Cognitive Network Framework for

Heterogeneous Wireless Mesh Systems

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This thesis is submitted in fulfilment of the requirement of the degree of

Doctor of Philosophy

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ABSTRACT

Heterogeneous wireless mesh networks (WMN) provide an opportunity to secure higher network capacity, wider coverage and higher quality of service (QoS). However, heterogeneous systems are complex to configure because of the high diversity of associated devices and resources. This thesis introduces a novel cognitive network framework that allows the integration of WMNs with long-term evolution (LTE) networks so that none of the overlapped frequency bands are used. The framework consists of three novel systems: the QoS metrics management system, the heterogeneous network management system and the routing decision-making system. The novelty of the QoS metrics management system is that it introduces a new routing metric for multi-hop wireless networks by developing a new rate adaptation algorithm. This system directly addresses the interference between neighbouring nodes, which has not been addressed in previous research on rate adaptation for WMN. The results indicated that there was a significant improvement in the system throughput by as much as to 90%. The routing decision-making system introduces two novel methods to select the transmission technology in heterogeneous nodes: the cognitive heterogeneous routing (CHR) system and the semantic reasoning system. The CHR method is used to develop a novel reinforcement learning algorithm to optimise the selection of transmission technology on wireless heterogeneous nodes by learning from previous actions. The semantic reasoning method uses ontologies and fuzzy-based semantic reasoning to facilitate the dynamic addition of new network types to the heterogeneous network. The simulation results showed that the heterogeneous network outperformed the benchmark networks by up to 200% of the network throughput.

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List of Abbreviations

3GPP	3rd Generation Partnership Project
AARF	Adaptive auto rate fall-back
AHP	Analytic hierarchy process
AI	Artificial intelligence
AMARF	Adaptive multi-rate auto rate fall-back
ANOVA	An Analysis of variance
AODV	Ad-hoc on-demand distance vector
API	Application program interface
ARF	Auto rate fall-back
CARA	Collision-aware rate adaptation
CBR	Constant bit rate
CCH	Control channel
CSC	Channel switching cost
CSMA/CA	Carrier-sense multiple access with collision avoidance
CTS	Clear to send

CCTAE	Computer and Communication Technologies in Agriculture Engineering
CHR	Cognitive heterogeneous routing
CQI	Channel quality index
DCF	Distributed coordination function
DREAM	Distance routing effect algorithm for mobility
DSDV	Destination-sequenced distance vector
DSR	Dynamic source routing
DSRC	Dedicated short range communication
eNB/eNodeB	Evolved node b
EPC	Evolved packet core
ETT	Expected transmission time
ETX	Expected transmission count
GPS	Global positioning system
GUI	Graphical user interface
IoT	Internet of Thing
IP	Internet protocol

IRU	Interference aware resource usage
ISM	Industrial, scientific and medical
LCD	Link connectivity duration
LSD	Least significant difference
LTE	Long term evolution
MCS	Modulation and coding scheme
MDPU	MAC protocol data unit
MIC	Interference and channel switching metric
MIH	Media independent handover
MIMO	Multiple in and multiple out
MME	Mobility management entity
MutFed	Mutual-feedback rate adaptation
NP	Non-deterministic polynomial-time
OLSR	Optimised link state routing
OWL	Ontology web language
P-GW	Protocol data network gateway

QoS	Quality of service
RAN	Radio access network
RARE	Rate adaptation algorithm based on reinforcement
RB	Resource block
RDF	Resource description framework
REFOT	Relative fairness and optimised throughput
RLC	Radio link control
RERR	Route error
RREP	Route response
RREQ	Route request
RTS	Request to send
S-GW	Serving gateway
SCH	Service channel
SINR	Signal-to-interference-to-noise ratio
TA-ARA	Traffic-aware active link rate adaptation
TARA	Throughput-aware rate adaptation

UDP	User datagram protocol
UE	User equipment
VANET	Vehicular ad-hoc network
V2I	Vehicle to infrastructure
V2V	Vehicle to vehicle
WAVE	Wireless access in vehicular environments
WMN	Wireless mesh network
WSN	Wireless sensor networks
WSW	Weight to select the Wi-Fi

List of Notations

Variable	Variable description
Φ	A set of all available nodes in the network, $d \in \Phi$
α	Learning rate of reinforcement learning
$BufL^d(t_i)$	Number of packets in the LTE transmission buffer for node $d \in \Phi$ at time t_i
$BufL_{max}$	Maximum number of packets that the transmission buffer of LTE device can accept
$CQW^d(t_i)$	Wi-Fi channel quality for node $d \in \Phi$ at time t_i
d	A heterogeneous network node
Exp	Boolean variable indicating whether the algorithm is in exploration mode
$Expcount$	Number of exploration cycles completed
$expThr$	Maximum number of explorations allowed
F	Number of consecutive transmissions failure on the node
$FlagW$	Boolean variable indicating whether the Wi-Fi device has been used
FLC	Fuzzy set of the LTE channel quality
FLL	Fuzzy set of the LTE load
$FR^d(t_{i-1}, t_i)$	Failure rate of a wireless node $d \in \Phi$
FWC	Fuzzy set of the Wi-Fi channel transmission rate
FWS	Fuzzy set of the Wi-Fi success rate
$IQ^d(t_i)$	Instantaneous queue length of node $d \in \Phi$
$LCD_{i,j}$	Lifetime of communication link between nodes i and j
LCD_{th}	LCD threshold value (in this work, 30 s is used)
$LL^d(t_i)$	Estimated LTE load on heterogeneous node $d \in \Phi$ at time t_i

$LP^d(t_{i-1}, t_i)$	Probability of accessing the shared channel for node $d \in \Phi$
$LQ^d(t_{i-1,},t_i)$	Link quality of node $d \in \Phi$
LSW	LTE strength weight
$LTEL^d_t$	LTE device load for node $d \in \Phi$ at time t
MaxQL	The physical maximum queue length
MaxQthr	Maximum queue threshold
MDPU	MAC protocol data unit
MinQthr	Minimum queue threshold
MissedPkt	Number of unsuccessful transmissions till current time (t_i)
$R(t_i)$	Reward at time t_i
$Rate^d$	Current data rate of node $d \in \Phi$
RAND	RAN decision
RB^d_t	Number of allocated resource blocks for node $d \in \Phi$ at time t
RBMax	Number of available resource blocks of the LTE cell
$RW^d(t_i)$	Transmission rate for node $d \in \Phi$ in the Wi-Fi device at time t_i
RW_{max}	Maximum transmission rate that the Wi-Fi transmission technology can support
S	Number of consecutive transmissions successful
SendData	Total number of transmission till current time (t_i)
$SRL^d(t_{i-1}\text{-}t_i)$	Success rate of node $d \in \Phi$ to access the LTE network since the last update of the probability to access LTE channel
$SRW^d(t_{i-1}\text{-}t_i)$	Success rate of node $d \in \Phi$ to access the Wi-Fi network since the last update of the probability to access Wi-Fi channel
$STL^d(t_{i-1}\text{-}t_i)$	Number of successful transmissions on the LTE device for node $d \in \Phi$ since the last update of the probability to access LTE channel
$STW^d(t_{i-1}\text{-}t_i)$	Number of successful transmissions on the Wi-Fi device for node $d \in \Phi$ since the last update of the probability to access Wi-Fi channel

t_i	Represent the current time instance
t_{i-1}	Represent the previous time instance of t_i
$TTL^d(t_{i-1}\text{-}t_i)$	Total number of transmissions using the LTE for node $d \epsilon \Phi$ since the last update of the probability to access LTE channel
$TTW^d(t_{i-1}\text{-}t_i)$	Total number of transmissions using the Wi-Fi for node $d \epsilon \Phi$ since the last update of the probability to access Wi-Fi channel
$Q^d(t_i)$	Statues of wireless channel for node $d \epsilon \Phi$
$QL^d(t_i)$	Probability of accessing the LTE channel for node $d \epsilon \Phi$ at time t_i
$Qlen^d$	Average queue length of node $d \epsilon \Phi$
$QW^d(t_i)$	Probability of accessing the Wi-Fi channel for node $d \epsilon \Phi$ at time t_i
V	A set of nodes that share the communication channel, $j \epsilon V$
WSW	Wi-Fi strength weight

List of Publications

Journal articles:

Ahmed Al-Saadi, Rossi Setchi, and Yulia Hicks and Stuart Allen, “Routing Protocol for the Next Generation of Heterogeneous Wireless Mesh Networks,” IEEE Transactions on Vehicular Technology, Issue: 99, pp 1-15, 2016.

Ahmed Al-Saadi, Rossi Setchi, Yulia Hicks, “Semantic Reasoning in Cognitive Networks for Heterogeneous Wireless Mesh Systems”, *Submitted to IEEE Transactions on Cognitive Communication and network*.

Conference proceedings:

Ahmed Al-Saadi, Rossi Setchi, Yulia Hicks and Stuart Allen, “Multi-Rate Medium Access Protocol Based on Reinforcement Learning”, IEEE SMC, pp 2875 – 2880, San Diego, USA, 2014.

Ahmed Al-Saadi, Rossi Setchi, Yulia Hicks, “Cognitive network framework for heterogeneous wireless networks”, Procedia Computer Science, vol. 60, pp 216–225, Singapore, 2015.

Chapter 1

Introduction

1.1 Introduction to Communication Networks

Communication networks can be categorised based on whether the transmission medium is a wired or wireless network. The wired network connects devices to other networks using cables; one of the most well-known example of this type is the local area network that known as the Ethernet. The wireless network is defined as a network that uses radio frequency bands to connect devices such as smartphones to the Internet or to a private business network. The frequency bands in telecommunications are defined as a specific range of frequencies in the radio spectrum. Because the simultaneous use of the same frequency band can cause interference and result in data loss, frequency usage is regulated by the International Telecommunication Union (ITU).

Among many of the successfully deployed wireless networks, cellular and multi-hop Wi-Fi-based networks are two of the most promising technologies. cellular network is led by ITU and the 3rd Generation Partnership Project (3GPP), which focuses on delivering high quality services to mobile users. The other is led by the Institute of Electrical and Electronics Engineers (IEEE), which emphasises the ease of access to the network.

Cellular networks include a set of terrain areas called cells, each of which is served by at least one fixed base station (BS). Each cell uses different frequency bands to avoid interference and guarantee the bandwidth. A cellular network provides large coverage to fixed and mobile devices, such as mobile phones, laptops, tablets, etc. The concept of cellular networks follows gradual trends, which started with the first generation (1G) and led to the current fourth generation (4G). Long-term evolution advanced (LTE-A) (3GPP TS 36.211 V8.7.0 2009) is considered the real 4G network. LTE-A was standardised by 3GPP and approved by the ITU. LTE-A networks consist of two main parts: the LTE base station, or evolved Node B (eNodeB or eNB) base station, and the evolved packet core (EPC). The eNB provides cell coverage, radio resource management and connection mobility management. The purpose of the EPC, which was first introduced by 3GPP in Release 8 of the standard, is to handle the network data traffic efficiently from the perspective of cost and performance.

Multi-hop wireless networks employ Wi-Fi to establish a network without a centralised infrastructure. The data unit, which is known as a packet, is transmitted by forwarding data from one node to another until they reach their destination; each node represents one hop count. A wireless mesh network (WMN) is a multi-hop wireless network that establishes a metropolitan area network. The WMN consists of three types of nodes: gateway, mesh and client. The gateway node has a high-speed wired connection to the Internet; mesh nodes are used as relay nodes to propagate data to and from the gateway; client nodes are devices that seek a connection to the Internet, such as mobile devices, laptops, etc. The packets are transmitted from one mesh node to another until they reach the gateway. In WMN, routing algorithms are developed to calculate the path for transmitting data from the source to the destination that optimises the network's performance.

Another important part of computer networks comprises the communication protocols, which use a set of rules to enable computer-based devices to communicate with each other. These protocols work as a set of network layers that are known as a network protocol stack to enable network capabilities. The protocols at each layer are mutually agreed on the format of performing functions. Figure 1.1 shows a block diagram of two nodes that use the transport control protocol / internet protocol (TCP/IP) network layers to communicate with each other. The application layer handles the details of the particular application. The hypertext transfer protocol (HTTP) and file transfer protocol (FTP) are examples of application layer protocols. The transport layer provides the end-to-end data transfer by delivering data from one application to its remote peer. The most frequently used transport layer protocol is TCP. The network layer, also known as the Internet layer, is responsible for routing data packets and forming the network; it shields the upper layer from the physical network. The Internet protocol (IP) is the most important protocol in this layer. The last layer is the physical layer, which is the actual interface with the physical hardware that is responsible for sending data through the network.

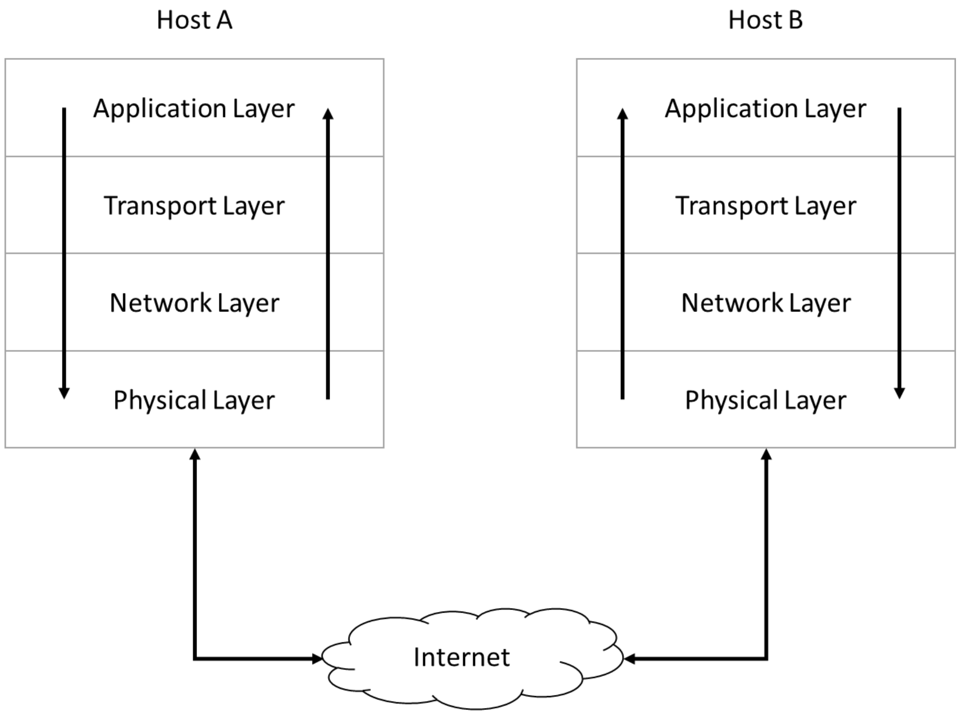

Figure 1-1: TCP/IP network layers

1.2 Motivation

Over the next three years, Internet traffic is expected to increase three to five times because of the growing number of connected mobile devices. Within the next decade, a more advanced Internet infrastructure will be required to support this increase in Internet traffic (Huawei 2014).

Next-generation wireless networks must overcome several challenges, including the cost to cover high-density areas, crowded events and large areas and to respond to temporary fluctuations in demand, for example, at a large sporting event. The cost estimation depends on the number of required base stations and the cost to rent frequency bands. Interoperability is another challenge as many devices use different operating systems, protocols and access technologies. Network reliability is also an important issue that needs to be addressed to ensure that systems are able to tolerate faults or interruption to the service in case of disasters (IWPC 2014).

The use of heterogeneous technologies, such as cellular and Wi-Fi networks improves the overall network performance by distributing the load across different network technologies (Hu et al. 2012; Yang et al. 2013; Hagos and Kapitza 2013), which provides an opportunity for higher network capacity, wider coverage and higher quality of service (QoS). However, the process of developing heterogeneous wireless networks is a very challenging task because each network type uses a different radio access network (RAN), has different standards and depends on various QoS parameters. Furthermore, routing packets through a heterogeneous network requires a new mechanism to exchange control messages among the different networks. The design of heterogeneous systems is highly complex because of the diversity of associated devices and resources, as well as the dynamic form of the network (Liu et al. 2013).

The internetworking of different wireless technologies, particularly the LTE network and the IEEE 802.11-based wireless mesh network (WMN), is one of the key opportunities involved in developing the next-generation wireless networks. The use of a WMN increases the network capacity by utilising unlicensed frequency bands, which reduce the cost of buying more LTE licensed frequency. The LTE network is used to avoid low-quality Wi-Fi links and it can connect island nodes if a link failure occurs.

LTE networks provide wide coverage and a peak transmission rate ranging from 100–326.4 Mbps on the downlink (from base station to user equipment) and 50–86.4 Mbps on the uplink (from user equipment to base station) depending on the antenna configuration and modulation depth. Due to the advanced technologies employed in the LTE networks, they can be used by major mobile operators around the world to cope with the high traffic demands. However, LTE networks use licensed frequency bands, which means that costs are incurred to provide more bandwidths through buying more frequency bands (which may not be available in all regions) or through investing in a higher density of base stations.

The WMN is a paradigm that was developed to provide wide network coverage without using the centralised infrastructure (Akyildiz et al. 2005). Therefore, WMNs are a feasible choice to provide a backbone network for metropolitan area networks (MANs). Gateways, which are wireless nodes that have a high-speed wired connection to the external Internet, are used to connect the WMN to the Internet. This architecture offers a cost-effective, ubiquitous wireless connection to the Internet in large areas through multi-hop transmissions to and from the gateway. However, the major drawbacks of using WMNs are their limitations in terms of capacity, system performance and guaranteed wireless link quality. The causes of these limitations originate from the multi-hop nature of the network. When data packets traverse a greater number of hops in a large WMN, either they can fail to reach their destination or they consume too many network resources. Moreover, in the case of a link or node failure, some nodes become isolated from the network because of the lack of a path to the destination or gateway, and form an *island node*.

One possible way to simplify the complexity of heterogeneous wireless networks is to employ cognitive networks. A cognitive network utilises network characteristics as input and extends network services by developing reasoning mechanisms for simplifying the complexity of managing modern wireless networks and enhancing network performance (Thomas 2007). The general issue with cognitive networks is finding the actions that move the network from a current situation to a desired situation, which tends to be a non-deterministic polynomial-time (NP) hard problem (Facchini 2011). The problem that the cognitive network model faces in heterogeneous WMNs is challenging because of the need to secure the QoS characteristics of multiple network architectures and to find the optimal solution using reasoning mechanisms.

The use of semantic technologies as a part of the cognitive network could establish a method to describe, annotate and create relationships of various QoS parameters and network characteristics. The integration of different artificial intelligence (AI) algorithms in the reasoning system would allow the automatic processing of the network operations, including optimisation, configuration and management. The introduction of AI-based systems in self-organised mobile networks offers an effective way toward developing smart future mobile networks (Wang et al. 2015). The use of a semantic based system enables each node in the heterogeneous network to be self-configured and aware of the surrounding environment and any additionally installed transmission devices.

1.3 Aim and Objectives

The aim of this research is to develop a novel heterogeneous wireless mesh networks architecture based on using LTE and WMN to improve the overall network capacity, link quality and coverage. This is achieved by developing a smart system for configuring, optimising and managing heterogeneous wireless mesh networks autonomously and facilitating the process of extending this network automatically. The project aims to build a framework that models the various network architectures using semantic based system and establishes a technique to develop reasoning systems using AI algorithms.

The specific objectives necessary to achieve the aim are identified as:

- Creation of a cognitive network framework based on a semantic system to optimise, configure and manage heterogeneous wireless mesh network.
- Building a rate adaptation technique for WMN to mitigate the impact of interference.
- Creation of routing metric based on the transmission rate that reflects the quality of the shared transmission channel.
- Building a novel heterogeneous wireless mesh network architecture of WMN and LTE that overcomes the drawbacks of each transmission technology utilised in the network.
- Development and validation of a new heterogeneous wireless mesh routing protocol that prescribes the required control messages and routing tables to enable the communication of heterogeneous transmission devices.
- Development of a new route selection algorithm to select transmission device to optimise the heterogeneous network performance.
- Development of a new semantic knowledge base system that simplifies the process of capturing the parameters of the heterogeneous systems from different layers of the network protocol stack through the use of ontologies and semantic rules.
- Establishing a semantic inference engine to configure different communication systems automatically and optimise the network performance without a need to customise the software of the transmission device or update other layers of the Internet protocol stack.

1.4 Thesis Outline

This thesis is organised into the following structure:

Chapter 1 has provided an introduction to the work.

Chapter 2 has introduced a state of the art review of wireless network architectures and discusses related work in the field. It also reviews the relevant literature in the area of rate adaptation algorithms in wireless local network, the related work in the scope of heterogeneous wireless networks, reinforcement learning and fuzzy inference, semantic web and ontologies.

Chapter 3 has proposed a cognitive network framework for optimising, configuring, and managing the heterogeneous wireless mesh network.

Chapter 4 has introduced a new rate adaptation algorithm for wireless mesh networks.

Chapter 5 has proposed a novel heterogeneous wireless mesh network architecture that utilises WMN and LTE networks; it also has introduced a new heterogeneous routing protocol and routing selection algorithm based on reinforcement learning.

Chapter 6 has used the developed heterogeneous WMN architecture to define an ontology based system to model and represent the heterogeneous wireless mesh network and also developed a reasoning system based on fuzzy controller to facilitate the process of configuring and optimising other wireless network architectures.

Chapter 7 highlights the contributions, limitations, and conclusions of this thesis, and proposes further work.

Chapter 2

Literature Review

This chapter reviews the state of the art in the research areas relevant to the work presented in this thesis. Initially, the wireless technologies and network architectures utilised in this research are discussed with detailed examples in Section 2.1. Section 2.2 highlights the existing work on WMNs; section 2.3 examines the rate adaptation algorithms in wireless local network; section 2.4 discusses the related work in the scope of heterogeneous wireless networks. Section 2.5 discusses the cognitive network, which is followed by a review about employing semantic web and ontologies for wireless networks in section 2.6. Then the reviews of the concepts related to reinforcement learning and fuzzy interference are presented in section 2.7 and 2.8 respectively. Finally, Section 2.9 summarises the findings and concludes the Chapter.

2.1 Wireless Networks

This section introduces the communication systems that this research utilises to create the proposed heterogeneous network architectures.

2.1.1 IEEE 802.11 Wireless LANs

IEEE 802.11 is a set of standards that was developed by IEEE standard committee (802) (Std, IEEE Committee 1990). The IEEE 802.11 standard defines a medium access control (MAC) layer and multiple physical layer specifications. The MAC defines the addressing and channel access mechanisms to make it possible for several network nodes to communicate with each other. The MAC layer acts as an interface between the physical layer that is responsible to set frequency bands, transmission power and the upper layers. The channel access mechanism in IEEE MAC is based on carrier-sense multiple access with collision avoidance (CSMA/CA) and a distributed coordination function (DCF). The transmission medium is shared among multiple nodes. CSMA/CA is used to prevent collisions before they occur. When the station has a packet to be sent, it checks the transmission medium. If the link is busy, it defers the transmission for a random period and then checks the link again. The DCF function specifies a random waiting time for each node, and then the node transmits a request to send message (RTS), and if it is cleared to send (CTS) the node transmits its packet. This approach minimises the possibility that more than one node checks the channel simultaneously.

IEEE 802.11, commonly known as Wi-Fi, provides low-cost, convenient and high transmitting speed technology. It has already been deployed in many hotspots, including airports, libraries, coffee houses and hotels. Wi-Fi uses unlicensed frequency bands, which means it is not necessary to pay for bandwidth; however, this attribute also increases the possibility of interfering with other neighbouring networks. Wi-Fi provides good indoor coverage. Moreover, the chipset price of Wi-Fi is dropping continuously, making it an economical networking option that is included in an increasing number of devices. Wi-Fi offers a data rate up to 780 Mbps in the IEEE 802.11ac, and the bandwidth is device-to-device transmission, which means that all the available bandwidth is allocated to the Wi-Fi node to transmit the incoming traffic. For example, if the available bandwidth for a Wi-Fi node is 54 Mbps, then the Wi-Fi node will utilise the entire bandwidth during the transmission without sharing it with neighbouring nodes.

IEEE 802.11 defines a number of different physical layer technologies. The first version operates in 2.4 GHz industrial, scientific and medical (ISM) bands and achieves 1 and 2 Mbps transmission. Several extensions were developed to provide a higher rate. The following are examples of the most common IEEE 802.11 extensions:

- IEEE 802.11b (IEEE Std 802.11b 1999) operates in a 2.4 GHz ISM band and achieves up to 11 Mbps.
- IEEE 802.11a (IEEE Std 802.11a 1999) operates in a 5 GHz ISM band with a data rate up to 54 Mbps.
- IEEE 802.11g (IEEE Std 802.11g 2003) achieves up to 54 Mbps in a 2.4 GHz ISM band.
- IEEE 802.11n operates at 2.4 and 5 GHz and increase transmission rate to more than 100 Mbps.
- IEEE 802.11ac (IEEE Std 802.11ac 2013) was developed based on the IEEE 802.11n to provide very high throughput that reaches 1 Gbps and is operated at frequencies lower than 6GHz.

Another approved standard is IEEE 802.11p, which adds wireless access in vehicular environments (WAVE) (IEEE Std 802.11p 2010). The standard is intended to support wireless access in vehicular ad hoc networks (VANETs), which exchange and broadcast safety-related service application data between moving vehicles, vehicle-to-vehicle

(V2V) units, or to roadside units, which is known as vehicle-to-infrastructure (V2I) communication. IEEE 802.11p operates in a dedicated short-range communication (DSRC) band of 5.85–5.92 GHz. In this band, one control channel (CCH) is used to transmit safety and control information, while up to six other service channels (SCH) are employed to exchange service information (IEEE Vehicular Technology Society 2006). Each vehicle periodically sends short messages (beacon) over CCH. Beacon signals are employed to announce the presence of the node to the neighbouring nodes and to provide the location and speed information. Figure 2.1 shows an example of a VANET multi-hop network.

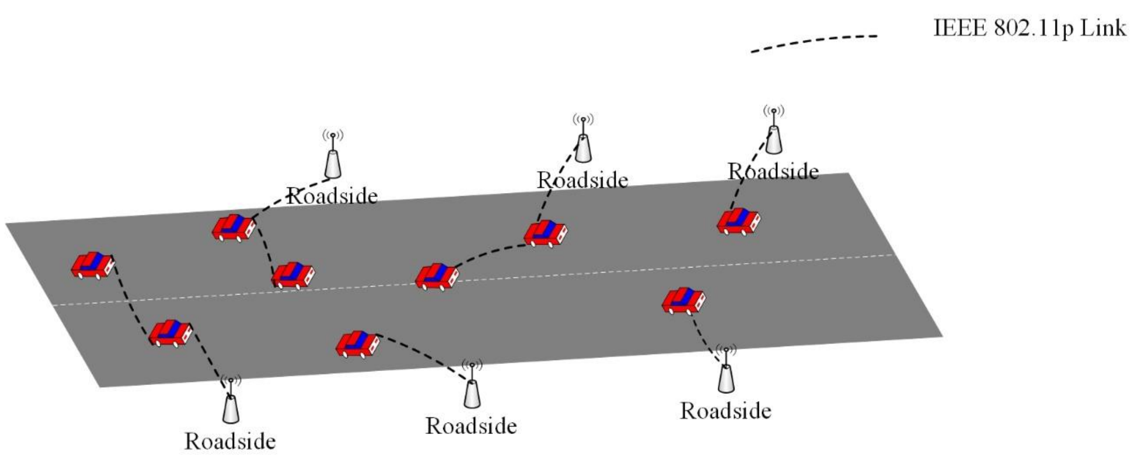

Figure 2-1: VANET network example

2.1.2 **Long-term Evolution (LTE)**

LTE (3GPP TS 36.211 V8.7.0 2009) was evolved from the 3G standard to improve the architecture of 3G cellular standards, such as UMTS and HSPA. It provides wide coverage and a peak transmission rate ranging from 100 to 326.4 Mbps on the downlink (from the base station to user equipment) and 50 to 86.4 Mbps on the uplink (from the user equipment to base station), depending on antenna configuration and modulation depth. The initial release (Release 8) was finished in 2007; currently, 4G is used to refer to this network.

The LTE network architecture involves an Internet protocol (IP) network architecture to provide low latency networks. The LTE network consists of two main parts: the evolved Node B (eNodeB /eNB) base station, which provides the cell coverage; and the evolved packet core (EPC), which connects the network to the Internet. Figure 2.2 shows a comprehensive illustration of the LTE network architecture. The EPC consists of three nodes: the protocol data network gateway (P-GW), the serving gateway (S-GW) and the mobility management entity (MME). The P-GW is the gateway to external IP networks, such as the Internet. The S-GW connects and routes the packets between the user equipment (UE). The MME is the signalling system that handles the node’s mobility and security in the Internet (Amate 2014).

The bandwidth in the LTE network is represented by the total number of resource blocks (RB) that are available for the user equipment in the network. The basic unit in each RB is the resource element (RE). RE represents one symbol by one subcarrier, which usually carries two, four or six physical channel bits, depending on the utilised modulation scheme. Each UE could allocate more than one RB based on the available bandwidth of the LTE network.

Because of the advanced technologies employed in LTE networks, they are used by major mobile operators around the world to cope with high traffic demands. However, because LTE networks operate licensed frequency bands, to provide greater bandwidth, an additional cost is introduced to buy additional frequency bands (which may not be available in all regions) or to invest in a higher density of base stations.

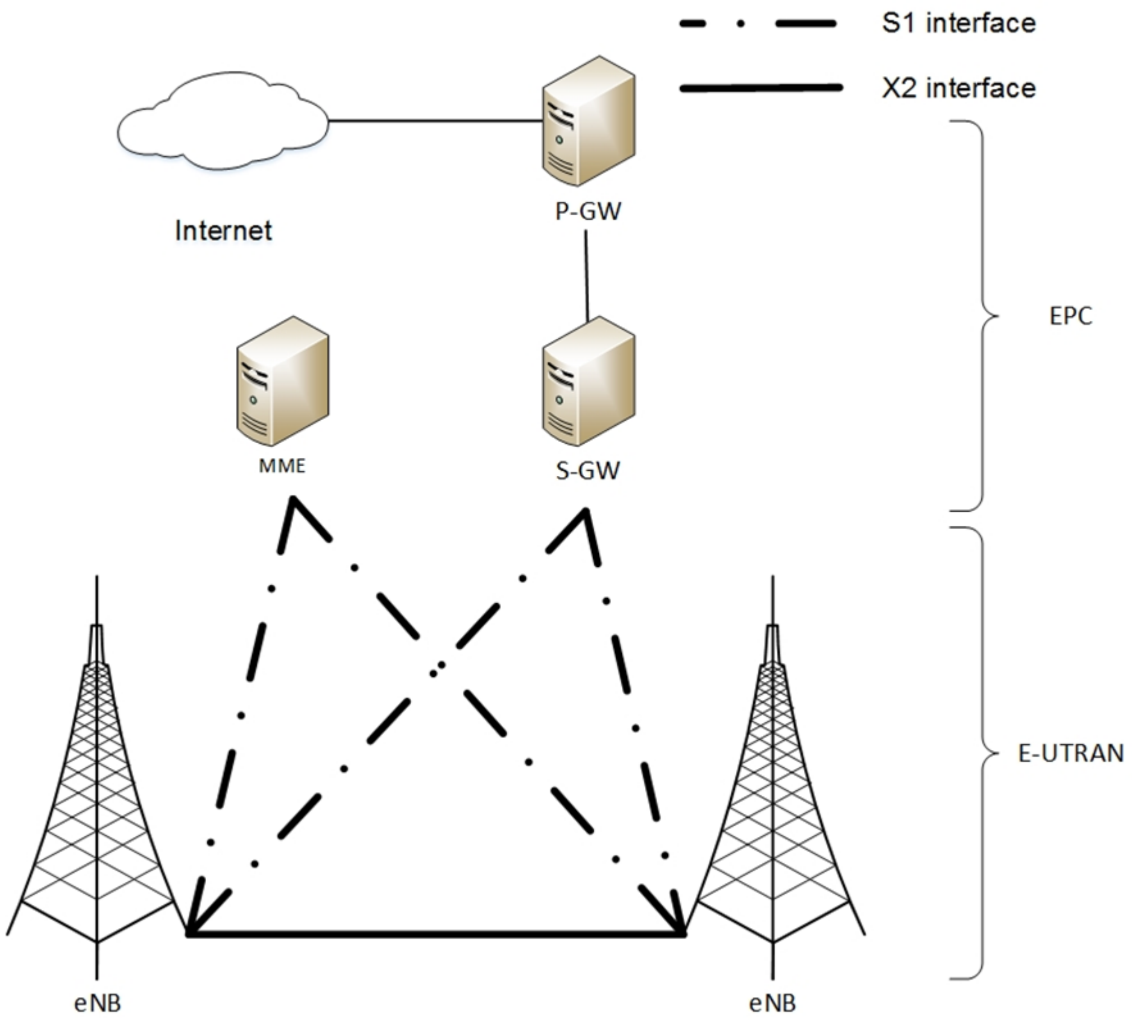

Figure 2-2: LTE network architecture (Firmin and 3GPP MCC 2014)

2.2 Wireless Mesh Network

The WMN paradigm was developed to provide broad network coverage without using a centralised infrastructure (Akyildiz et al. 2005). In such networks, nodes are used as relays to propagate data from the source to the destination using multi-hop paths to provide service to users. A mesh node can obtain Internet connectivity through a multi-hop path from a mesh gateway, which results in congestion at both the gateway and the nodes close to the gateway.

The mesh network provides an appropriate choice to create the infrastructure for metropolitan area networks (MAN). WMNs typically employ IEEE 802.11 to provide an economical approach to indoor and outdoor broadband wireless networks. This network architecture has been deployed in many cities and rural areas worldwide, such as New Orleans, Seattle, Ghana and Zambia (Zhao 2011). Figure 2.3 shows an example of WMN architecture.

Routing protocols and routing metrics have a significant impact on the performance of WMNs. Therefore, this section discusses related works on different routing protocols and metrics in WMNs.

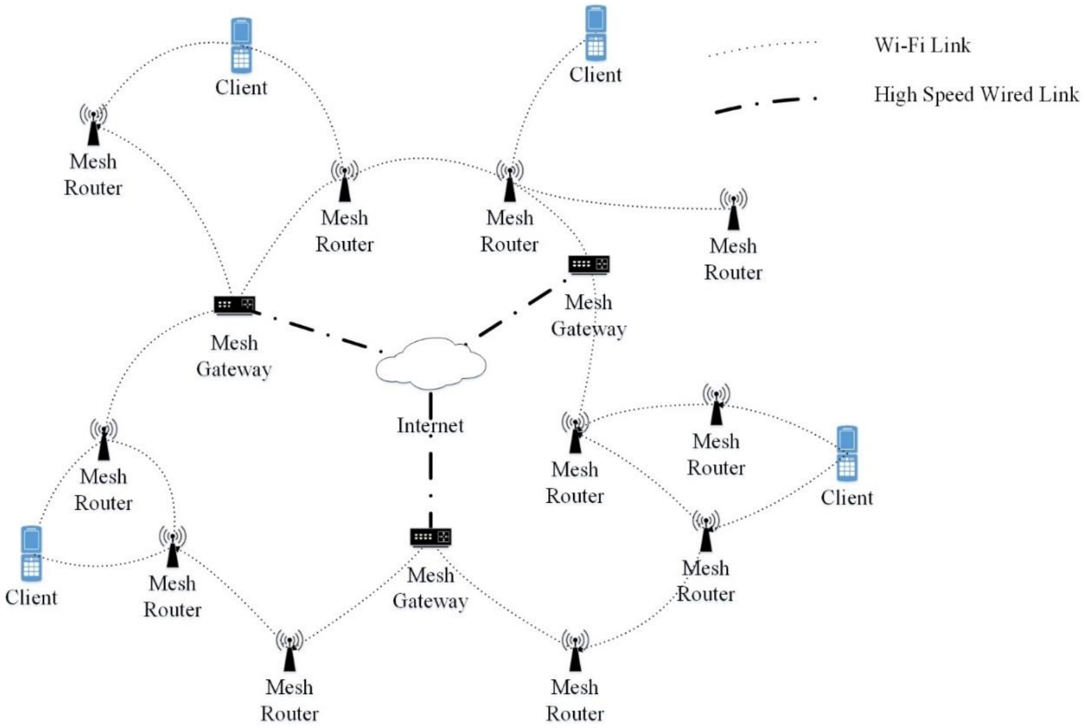

Figure 2-3: WMN architecture

2.2.1 **Routing Protocols in WMNs**

There are two types of routing protocols in WMNs. The first type consists of reactive routing protocols in which the route is created on demand by flooding the network with route requests. The route selection is maintained only for nodes that transmit traffic to a particular destination. Examples of this type of routing are ad hoc on-demand distance vector (AODV) (Perkins et al. 1999) and dynamic source routing (DSR) (Johnson et al. 2001). Reactive routing causes some delays because a route is created only when there are data ready to be sent. Three types of packets are employed in reactive routing, which use the following:

- Route request packet (RREQ) floods the network when a node has data packets that need to be sent.
- Route response packet (RREP) is unicasted to the originator node that contains the full path to the destination.
- Route error packet (RERR) is sent when a route to the destination fails.

The second type of routing protocol consists of proactive or table-driven routing protocols. They maintain a table of the entire destination in the network by periodically distributing an update of the routing table to all nodes. Destination-sequenced distance vector (DSDV) (Perkins and Bhagwat 1994) and optimised link state routing (OLSR) (Jacquet et al. 2001) are examples of this type of routing protocol. The route table maintains the route to each destination; transmission begins with no delay if packets are ready to be sent. However, some overhead is added to distribute routing table information among the nodes in the network. Hybrid routing protocols combine reactive and proactive routing to reduce the overhead of route discovery by employing proactive routing to nearby nodes and generating routes to distant nodes by using on-demand routing (Abolhasan et al. 2003). The zone routing protocol (Haas and Pearlman 1983) and distance routing effect algorithm for mobility (DREAM) (Stefano et al. 1998) are examples of hybrid routing protocols.

2.2.2 Routing Metrics in WMNs

The most widely utilised metrics in WMNs routing protocols select the shortest path to the gateway based on the hop count. Many ad hoc routing protocols, such as AODV (Perkins et al. 1999), DSR (Johnson et al. 2001) and OLSR (Jacquet et al. 2001), employ this routing metric to find the shortest path from the source to the destination. This approach considers the minimum number of hops from the sender to the receiver. However, prior research has recognised a shortcoming in hop count metrics in WMNs: the shortest path metric results in a congested path (Mogaibel and Othman 2009). Moreover, a smaller number of hops may lead to a poor-quality link because the metric does not consider QoS parameters such as delay, bandwidth, link quality or transmission rate (Ahmeda and Esseid 2010; Zhao and Al-dubai 2012). Therefore, many researchers have employed quality-aware metrics, which dynamically evaluate link quality characteristics to improve network performance. Some of these metrics employ a link loss ratio to select the path to the gateway. One of the most widely cited measures is the expected transmission count (ETX) (De Couto et al. 2003), which estimates the required number of transmissions for the successful data delivery between two nodes. However, ETX does not consider the bandwidth, the packet size, or the link interference; therefore, the metric does not perform well on a network that has a high transmission rate and a large packet size. The ETX value can be calculated as follows:

$$ETX = \frac{1}{df * dr}, \tag{2.1}$$

where *df* is the measured probability that a data packet is successfully received by the receiver, and *dr* is the likelihood of receiving an acknowledgement by the sender. Expected transmission time (ETT) (Draves et al. 2004) enhances ETX by considering the packet size and the link bandwidth in calculating the metric. However, this metric does not consider the load and link interference. Equation (2.2) is used to calculate ETT value:

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

where *S* is the packet size and *B* is the available bandwidth. The interference and channel switching (MIC) metric (Yang et al. 2005) was proposed as an alternative to the ETT. MIC is topology-dependent and selects paths with a minimum number of nodes that share the wireless channel. However, MIC fails to indicate whether the interferer node has data to transmit, as the interferer cannot cause interference when there is no transmission. MIC is calculated using the following equation:

$$MIC(p) = \frac{1}{N * \min(ETT)} \sum_{link\ l \in p} IRU_l + \sum_{node\ i \in p} CSC_i, \tag{2.3}$$

where *p* is a path in the network, *IRU* is interference aware resource usage for link *l* on the path *p*, and *CSC is* the channel switching cost for node *i* that belongs to path *p*.

Another routing metric is used to estimate the available bandwidth on the network. Bandwidth can be defined as the amount of data that flows through the network (Zhao

2011). Determining the available bandwidth on IEEE 802.11 medium access control (MAC) is challenging because the channel is shared among the neighbouring nodes, and the surrounding environment changes frequently (Peng et al. 2013). One method that is used to estimate the available bandwidth is to listen passively to the channel in order to determine the busy time and the idle time (Chen and Heinzelman 2005; Ramadhan 2010; Peng et al. 2013). When the channel state changes from idle to busy (i.e., the channel is sending or receiving), the node computes the busy time and the idle time during period *T*. The available bandwidth is calculated using the following equation:

$$B(k) = Craw(k) * \frac{Tidle}{T}, \tag{2.4}$$

where *B(k)* is the estimated available bandwidth, *Craw(k)* is the physical capacity of channel *k,* and *Tidle* is the calculated idle time during time slot *T*.

Another approach to estimating the available bandwidth is to exchange hello messages among the neighbouring nodes containing information that could be used to determine the available bandwidth on the network (Chen and Heinzelman 2005).

In WMN, gateways are employed to connect the network to the Internet. Gateway selection is one of the major problems in WMN because the majority of the traffic goes through the gateway, which causes congestion at these points. Some routing metrics consider gateway selection in calculating the routing path. An example of this parameter is employing a centralised online gateway selection to provide load balancing on the gateways (Galvez et al. 2012). The calculation of this metric consists of two stages: 1) the hop count metric is employed to measure the path cost to the gateway by setting a threshold for the distance to the gateway, and each node maintains a list of valid gateways; 2) the load on the gateway is computed using a central controller that could be any gateway in the network. The gateways collect network parameters and send them to the controller to perform the gateway selection algorithm. However, the central controller requires a wired network of gateways and the central controller. This wired network results in increasing the complexity of building the infrastructure to connect the gateways, which are usually located too far from each other to provide Internet connections in large areas.

Another key link characteristic is the transmission rate. IEEE 802.11 supports multiple transmission rates; for each rate, there is a different transmission range and a different interference range. Changing the transmission rate could improve the network performance to exploit scarce wireless resources optimally under unstable channel conditions. The rate adaptation algorithms are reviewed in the next section.

2.3 Transmission Rates in IEEE 802.11

IEEE 802.11 supports multiple transmission rates; for each rate, there is a different transmission range and a different interference range. The physical layer of IEEE 802.11 employs different modulation and coding techniques, which results in providing multiple transmission rates. By applying a higher transmission rate, the node sends data packets faster, which shortens the necessary transmission time and increases the throughput. However, a higher transmission rate requires a higher signal-to-interference-to-noise ratio (SINR) at the receiver in order to decode the packet successfully due to the utilised modulation scheme. Therefore, employing a higher transmission rate requires higher transmission power to meet the SINR needed on the receiver. In turn, this results in higher interference among other nearby nodes and thus reduces the overall network throughput.

Rate adaptation involves two main tasks: estimation of the channel condition and selection of the most applicable transmission rate. This section reviews existing rate adaptation techniques according to the metrics employed to adjust the transmission rate.

2.3.1 Rate Adaptation Based on Frame Loss Statistics

The first category is based on gathering transmission failure statistics on the sender side to estimate the interference level of the receiver side. If the transmission failure exceeds a given threshold, this means that the channel suffers from high interference, and the transmission rate is reduced.

The earliest rate adaptation of this category is auto rate fall-back (ARF) (Kamerman and Monteban 1997). This mechanism was developed for WaveLan II to enhance the application throughput. Each node starts with the basic rate (2 Mbps) and then sets a timer. If either the timer expires or N (a given threshold) consecutive successful transmissions take place, the node increases the transmission rate and resets the timer. If the new rate fails directly, or if there are two consecutive fails, the node decreases the rate.

Recent work in this area has proposed improving the performance of ARF by avoiding updating the transmission rate when the cause of transmission failure is not due to interference. Adaptive ARF (AARF) (Lacage et al. 2004) improves ARF by changing the threshold for switching the data rate adaptively. ONOE (MADWIFI, 2013) assigns credits to the rates based on the network statistics and selects a transmission rate with a loss ratio of less than 50%. Collision-aware rate adaptation (CARA) (Kim et al. 2006) enables requests to send/clear to send (RTS/CTS) handshaking messages of distributed coordination function (DCF) only when the number of transmission failures exceeds a certain threshold. Adaptive multi-rate ARF (AMARF) (Xi et al. 2006) assigns different success threshold for each data rate and uses these numbers as a criterion to switch the transmission rate.

The limitation of all these approaches of rate adaptation is that they do not distinguish between channel error and packet collision when there is a transmission failure. Moreover, these techniques do not take into account the competing nodes accessing shared channels in WMN and the congestion in those nodes.

2.3.2 Rate Adaptation Based on Traffic Estimation

These types of rate adaptation algorithms consider the traffic at the sending node and whether the current transmission rate can meet the traffic demand. Traffic-aware active link rate adaptation (TA-ARA) (Ao et al. 2010) and the method proposed in (Du et al. 2013) estimate the load on nodes by measuring the buffer length of each node and update the transmission rate based on the load in the node. The former updates the transmission power with the transmission rate while the latter keeps the transmission power constant. This type of rate adaptation can cause high interference in networks like WMN as it suffers from high congestion, especially in the nodes close to the gateway. Therefore, these approaches increase the transmission rate of nodes with high traffic loads, which results in high interference to the other nodes in the WMN.

2.3.3 Throughput-Aware Rate Adaptation

Throughput-aware rate adaptation algorithms predict throughput gain by updating the transmission rate and mitigating the bad impact of interference on the network. Relative fairness and optimised throughput (REFOT) (Benslimane and Rachedi 2014) achieves fairness among nodes in mobile ad hoc networks (MANET) while maintaining network throughput. Throughput-aware rate adaptation (TARA) (Ancillotti et al. 2009) selects the best transmission rate to provide higher throughput through estimating packet transmission times and network activity.

2.3.4 Receiver-Based Rate Adaptation

In receiver-based rate adaptation, the receiver station measures the channel state and sends feedback to the sender node to adjust the transmission rate according to the received feedback. Mutual-feedback rate adaptation (MutFed) (Khan and Mahmud 2010) measures the received signal power on the receiver node and selects the suitable transmission rate. Then, it sends the suggested transmission rate as a feedback to the sender. Upon receiving the feedback message, the transmitter may accept or decline the suggested transmission rate.

2.4 Heterogeneous Wireless Networks

This section discusses wireless networks that utilise different types of transmission technologies. The wireless networks are reviewed according to the way of employing heterogeneous transmission technologies in the network.

The first type of heterogeneous network in which the client is capable of using vertical handover. The vertical handover is the process of switching from one network to a different network to avoid congestion, poor channel quality, or to improve the QoS. Media independent handover (MIH) is proposed by the IEEE group (802.21) to provide a seamless vertical handover between different RAN (IEEE 802.21 Working Group 2009). IEEE 802.21 standard provides the link layer and other network information to the upper network layer to improve the handover in the heterogeneous networks. MIH is employed to provide handover between IEEE 802 family of standards, such as Wi-Fi and Wi-Max (Tamijetchelvy et al. 2012; Hamaydeh et al. 2013) or 3GPP network (Chu and Kim 2013). The decision of selecting the transmission technology is a crucial part of vertical handover; some work considers the user preferences as the most important parameter in selecting the network to carry out the communication (Gupta and Rohil 2013). While other algorithms consider QoS parameters in choosing the best network, for example, solving the problem of network congestion (Walid et al. 2014). Vertical handover in ad-hoc networks is another way to utilise different radio technology (such as Wi-Fi, Bluetooth and ZigBee) to improve frequency utilization, reduce interference and increase network capacity (Stuedi and Alonso 2005; Waheed and Karibasappa 2008; Le et al. 2010; Fujiwara et al. 2012).

Other types of heterogeneous networks split data among broadband and Wi-Fi wireless networks to increase network capacity. One approach is to distribute traffic among networks fairly (Yang et al. 2013) by employing load-balancing algorithms. Other architectures employ wireless characteristics to distribute data among networks. For instance, networks with better wall penetration are utilised for indoor communication such as Wi-Fi network while networks with higher frequency bands are employed for outside communication such as LTE or WiMAX (Hu et al. 2012; Hagos and Kapitza 2013). Traffic priority is employed to manage packets flow in heterogeneous networks

(Chen et al. 2010) in which only sensitive packets from the Wi-Fi network are forwarded through the cellular network to avoid weak links.

A cellular network is a mobile network that distributed over land areas called cells. A new architecture that combined cellular network with multi-hop Wi-Fi architecture is proposed to relay data packets for clients that suffer from low channel quality, or to offload a congested cell by forwarding the traffic to other non-congested cells (Wu et al. 2001; Li et al. 2002; Luo et al. 2003; Dixit and Yanmaz 2005). These networks utilise the multi-hop Wi-Fi network as an auxiliary network to redirect traffic from one cell to another.

IEEE 802.11-based vehicular ad hoc networks (VANETs) and LTE networks are employed to form a hybrid network in which some nodes in VANET are elected to work as a gateway to forward traffic demands to the LTE base stations (Tabbane et al. 2015; Taleb et al. 2015). The access network is selected based on a set of QoS parameters to improve the network performance throughout the mobile path of vehicles.

Other recent research aims to improve cellular networks by employing a mixture of macro cells and small cells, such as microcells, pico-cells, and femto-cells (Pantisano et al. 2012; Zhang 2012; Soh et al. 2013; Palanisamy and Nirmala 2013; Lin and Feng 2014; Soret and Pedersen 2015). The use of small cells improves the frequency reuse by employing lower transmission power, which produces less interference and increases the data rate of cellular networks. Wi-Fi access points are also utilised to create pico-cells to offload congested cells in cellular networks (Himayat et al. 2014).

A promising approach is to equip cellular base stations with different wireless access technologies and frequency bands to reduce the interference between neighbouring cells (Suga and Tafazolli 2013). The coverage of each base station is divided into a number of regions based on the modulation and coding scheme (MCS) utilised by each wireless technology in the base station.

2.5 Cognitive Networks

The cognitive network is a network paradigm that was recently developed to reduce network complexity and enhance network performance. Based on the literature, the cognitive networks have the following characteristics:

- Extensibility, flexibility, and proactivity;
- Their ability to use network metrics as input and produce an action to the network as output;
- The ability to improve network performance compared with traditional networks (Facchini 2011).

In cognitive networks, it is difficult to determine the actions that move the network from a current situation to a desired situation, which tends to be a non-deterministic polynomial-time (NP) -hard problem (Facchini 2011). The problem that a cognitive network model faces in heterogeneous WMNs is challenging because of the need to secure the quality of service (QoS) characteristics of multiple network architectures and to find the optimal solution using reasoning mechanisms.

The cognitive network process, which is known as a cognition loop, is represented in Figure 2.4 (Fortuna and Mohorcic 2009). The cognitive loop consists of six modules: Sense, Learn, Plan, Decide, Act and Environments. The network collects, gathers and pre-processes parameters to sense the environment (Sense). The information gathered by the Sense module is further used in planning the network functions (Plan) and then is

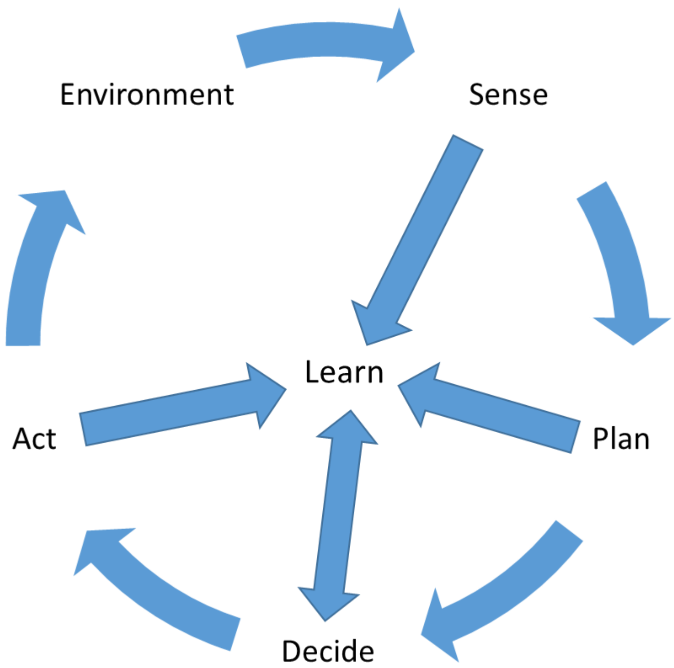

Figure 2-4: The cognition loop (Facchini 2011)

fed to learning stage (Learn) to aid the decision maker (Decide) in future actions. The planning module determines potential actions, such as selecting next hop in WMN or updating transmission power for the network based on observations. The decision module decides the possible moves based on the available actions and experience learned from previous actions. Then the Act module performs the selected action in the environment. The learning module is well connected with multiple modules (Sense, Plan, Decide and Act), so it can perform reasoning based on the knowledge acquired from different stages in the cognition loop.

Several studies (Thomas et al. 2006; Uchida et al. 2011; Li et al. 2013; Bennis et al. 2013; Lee et al. 2007; Rovcanin et al. 2014) showed examples of how the cognition loop is used to assess the current network conditions, and then to apply learning and artificial intelligence (AI) algorithms to decide future actions. For example, Uchida et al. (2011)

proposed a cognitive network for disaster situations in which a transmission device was used as a control device to exchange the network QoS parameters, and then an algorithm was developed based on the analytic hierarchy process (AHP) to select the most suitable link for handling traffic transmission. Other studies used reinforcement algorithms to create a cognitive process to mitigate the impact of interference in wireless networks (Li et al. 2013; Bennis et al. 2013; Rovcanin et al. 2014). For example, reinforcement learning can be employed in macrocells to collaborate and learn from other cells to reduce the power required by a macrocell base station and to enhance the coordination of inter-cell interference (Li et al. 2013; Bennis et al. 2013). Another study used reinforcement algorithms to create cooperation between different networks to avoid interference, such as activating or deactivating some services (Rovcanin et al. 2014).

2.6 Semantic Technologies

This part of the review introduces the principles of semantic technologies and ontologies and then discusses the use of these technologies in the wireless communication field, before highlighting the research gap in this area.

2.6.1 Ontology

As defined in (Gruber 1993), ontology is ‘a specification of a representational vocabulary for a shared domain of discourse’. It specifies the formal representation of types, properties and relationships among data in a given domain. Ontologies are used to create relationships between technology-dependent features. Inference engines, or reasoners, utilise the instances of ontologies in a knowledge base to infer the appropriate action to be taken based on a set of predefined rules. The data in the ontology are defined as a set of relationships between resources, whereas the reasoner infers new relationships based on the data and the rules. Figure 2.5 shows an example of using ontology classes and properties to represent network nodes. It shows Net class as the root class that represents the network and Node as a subclass of Net. Wi-Fi is a subclass of Node that has three properties: has_Neighbour, has_Address and has_DataRate. This example shows how ontologies use classes and properties to create relationships between different network components. Reasoning could be used to infer new relationships; for example, the "has_Neighbour" property could be used in a routing protocol to infer the one-hop count away from the node.

Standard ontology languages define a set of classes, subclasses, properties and relationships. The ontology is then employed to create an abstraction model for different classes and properties and create domain knowledge base. The most well-known languages are the resource description framework (RDF) (Klyne and Carroll 2004), RDF

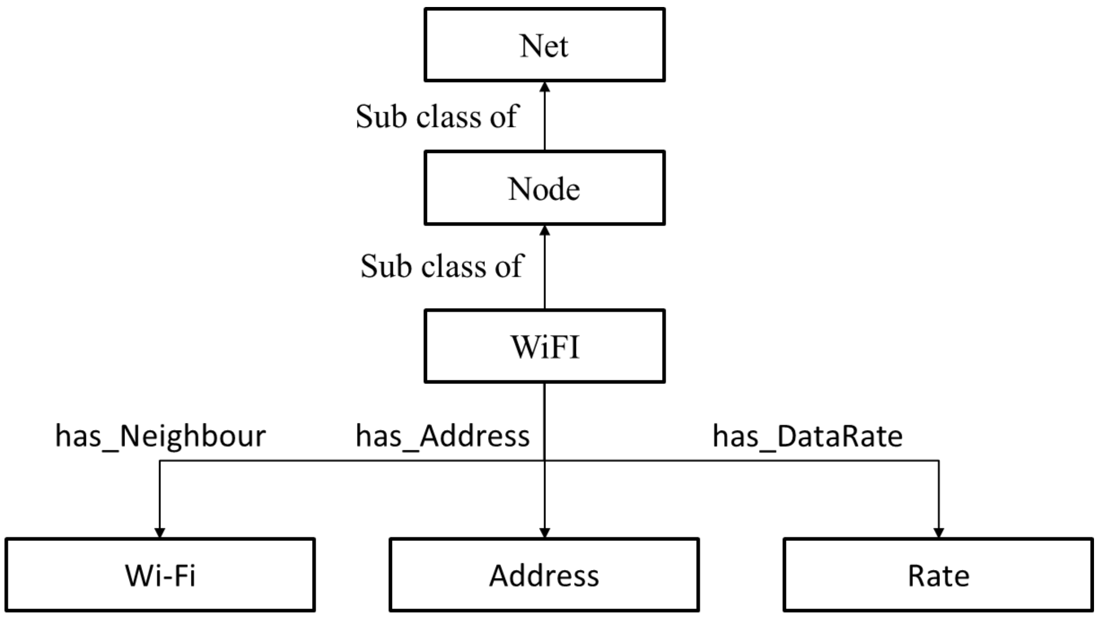

Figure 2-5: Ontology graph example

schema (Brickley and Guha 2000) and ontology web language (OWL) (McGuinness and Harmelen 2004).

RDF defines a set of assertions, or statements, which consist of three parts: subject, predicate and object. The subject is the thing being described, and the predicate is the relationship between the predicate and the object. RDF provides the ability to describe metadata and how they relate. RDFS defines the schema of the ontology, and it defines classes and properties to build the ontology schema. RDFS semantics (Hayes and Mcbride 2004) introduce some inference capabilities to the documents. OWL is a powerful ontology language that defines classes and different types of properties and allows for reasoning and consistency checking on the ontology. OWL inference (Patel-Schneider et al. 2004) provides powerful inference operations based on classes, subclasses, object and data properties. OWL 2 (W3C OWL Working Group 2012) is the extended version of OWL, and it has been standardised by the W3C group. OWL 2 extended OWL by providing the following features: property chains; richer data types, data ranges; qualified cardinality restrictions; asymmetric, reflexive, and disjoint properties; and enhanced annotation capabilities. OWL 2 is a very expressive computational language and is therefore very difficult to implement (Taylor 2014). OWL can be used to describe web services, and an extension to OWL was developed for the semantic web service (OWL-S) (Martin et al. 2004) used to describe web services. OWL-S is a computer-interpretable language that was developed to describe the web service. OWL-S is expected to enable automatic web service discovery, automatic web service invocation, and automatic web service composition and interoperation.

In this study, a light extensible mark-up language (XML) (Bray et al. n.d.) is employed to create the classes, subclasses, data and object properties, domains and ranges. XML is used for two reasons: First, XML is platform independent, which enables the use of the reasoning system proposed in this study on any smartphone, personal computer or computerised object. The second reason is that the ontology proposed in this work is relatively simple and does not need the extent of expressiveness that is provided by other standard ontology languages. XML is a simple, lightweight ontology system that can work on wireless nodes with limited processing resources. Figure 2.6 shows an example of an XML code that represents the ontology classes on a wireless node.

```
   ...
        <hasIpAddress>3.0.0.9</hasIpAddress>
        <hasMAC>03-06-00:00:00:00:00:18</hasMAC>
      </hasWiFiDevice>
    - <hasLTEDevice value="true">
        <hasIpAddress>7.0.0.5</hasIpAddress>
        <hasImsi>4</hasImsi>
      </hasLTEDevice>
      <hasNeighb/>
  </individual>
- <individual resource="Node" mine="false" id="13">
      <hasType>netNode</hasType>
    - <hasWiFiDevice value="true">
        <hasIpAddress>3.0.0.10</hasIpAddress>
        <hasMAC>03-06-00:00:00:00:00:19</hasMAC>
      </hasWiFiDevice>
    - <hasLTEDevice value="true">
        <hasIpAddress>7.0.0.6</hasIpAddress>
        <hasImsi>5</hasImsi>
      </hasLTEDevice>
      <hasNeighb/>
  </individual>
- <individual resource="Node" mine="false" id="14">
      <hasType>netNode</hasType>
    - <hasWiFiDevice value="true">
        <hasIpAddress>3.0.0.11</hasIpAddress>
        <hasMAC>03-06-00:00:00:00:00:1a</hasMAC>
      </hasWiFiDevice>
    - <hasLTEDevice value="true">
        <hasIpAddress>7.0.0.7</hasIpAddress>
        <hasImsi>6</hasImsi>

  ...
  ...
```

Figure 2-6: XML excerpt of a network ontology

The XML file represents the ontology classes and properties using XML tags, such as hasIPAddress property, to represent the IP address of the node class that is equipped with a Wi-Fi device.

2.6.2 Semantic Reasoning

Semantic reasoning consists of sets of facts and rules that infer local consequences. The data in the ontology are defined as a set of relationships between resources. The reasoner infers new relationships based on the data and the rules. Some reasoning systems have been developed to validate the ontology design, check the consistency of the relationships between ontology classes and regenerate these relationships (Horrocks and Voronkov 2006). This type of reasoning has been embedded as a plug-in in ontology designing tools, such as Protégé (Protégé 2003) and OilEd (Bechhofer et al. 2001).

2.6.3 Semantic Technologies for Wireless Networks

This section reviews advanced approaches to employing ontologies and knowledge engineering in wireless networks. It highlights the use of semantic technologies and ontologies in networking and wireless communication.

A number of studies (Kim et al. 2008; Jabeur et al. 2009; Iqbal et al. 2009; Ren and Jiang 2011; Liu and Xiong 2013; Xiong et al. 2014) used ontologies in wireless sensor networks (WSNs) by observing data from sensor nodes and using that data to build the ontology knowledge base. For example, ontologies and semantic reasoning are employed in routing algorithms for WSNs (Jabeur et al. 2009; Xiong et al. 2014) to select the next hop and forward data based on the data observed by sensors. For instance, if a heat sensor observes high temperature, the node adds semantic information, such as the location of the high-temperature area, to the feedback message. The reasoner in the neighbouring nodes uses the location information to avoid forwarding the data through the high-temperature area since there is a possibility of fire (Jabeur et al. 2009). Another routing algorithm utilises ontologies to describe node information, including node position, residual energy, communication distance, and detection distance, to understand the status of neighbouring nodes. If more than one node is available to perform the same task, then the node closest to the sink with the highest residual energy is selected to do the required work (Xiong et al. 2014).

Ontologies and semantic reasoning were also used to automatically find and access the services in WSNs (Kim et al. 2008; Iqbal et al. 2009; Ren and Jiang 2011; Liu and Xiong 2013). Examples include monitoring the service type of each node by collecting the data and service type in a cluster head node (Iqbal et al. 2009) or generating an abstraction model for the resource specification in the WSNs to present the characteristics of the network (Ren and Jiang 2011). Accessing the services in WSNs requires a semantic annotation of the available services, as well as binding these services with such network properties as service properties (temperature), location properties (the sensor node location), and physical properties (processor type and memory size), which aids the search and retrieval of the services requested by the end user (Kim et al. 2008; Liu and Xiong 2013).

Ontologies and semantic reasoning systems have also been used to assist with the management, specifically the topology discovery, of a heterogeneous, multi-tier network (Frye and Cheng 2010; Frye et al. 2014). If an ontology is developed for WSN, ad hoc, and wired networks, then another ontology can map the concepts from each ontology into a single common ontology. For example, network nodes can utilise different address types, such as an Internet protocol (IP) or node ID, and the address in each ontology can be mapped to a property in the common ontology. The properties of the network devices are retrieved by standard network management systems to create the instances in the knowledge base. Another research has used ontology web language (OWL)-S to develop network management systems (Vergara et al. 2005; Xu and Xiao 2006;Xu and Xiao 2007; Zhang et al. 2010). OWL-S specifies the data type using ontology classes to assign semantic meanings to the data retrieved from the network management system. The network manager can then deal with the ontology classes to indicate the network status using standard reasoning and querying systems.

Another use of ontology and semantic reasoning was in cognitive radio communication (Wang et al. 2003; He et al. 2010; Bahrak et al. 2012). The concept is to create wireless nodes that are capable of understanding the content of the information to be transferred, as well as the abilities of the node itself, the destination, and the environment. In this case, the node utilises ontology instances in the knowledge base to express understanding of its capabilities to meet the transmission needs, which helps to deduce the optimal operating parameters.

Although ontologies and semantic reasoning have been used in wireless communication systems, research on managing and optimizing heterogeneous networks using cross-layer parameters from different network architectures is still limited. Current communication systems utilise ontologies to represent information from the application layer to define a set of relationships and classes that could be used to improve network performance.

2.7 Reinforcement Learning

Reinforcement learning is a machine learning technique that aims to find the perfect action to perform in a dynamic environment (Kaelbling et al. 1996; Sutton and Barto 1998). It employs trial and error to evaluate the selected action and find the perfect action through a mathematical formulation. The Q-learning algorithm is one of the most well-known approaches to the reinforcement learning applied to wireless networks (Watkins and Dayan 1992). It does not need a model of its environment; instead, it predicts the future rewards for taking an action. In Q-learning, each time (t_i) an action is executed, a reward $R(t_i)$ is calculated based on feedback from the environment. Using (2.4), the agent Then re-computes the Q-value, which is subsequently used to re-estimate the best action. In Q-learning, each time (t_i) an action is executed, a reward $R(t_i)$ is calculated based on feedback from the environment. Equation (2.4) (Watkins and Dayan 1992) re-computes the Q-value, which is subsequently used to estimate the best action.

$$Q(t_i) = (1-\alpha)Q(t_{i-1}) + \alpha[R(t_i) + \gamma Q(i_{i+1}) - Q(t_{i-1})], \qquad (2.4)$$

where α is the learning rate ($0 \leq \alpha \leq 1$), t_i is the current time, t_{i-1} is the previous time for $i > 1$, and γ is the discount value. If $\alpha = 0$, then there is no learning in the algorithm; if $\gamma = 0$, the reinforcement learning is opportunistic, which maximises only the immediate, short term reward.

The Q-learning algorithm is one of the most well-known approaches to the reinforcement learning applied in wireless networks. In the present work, it is considered the best learning approach for the following reasons:

- The learning is based on trial and error, and no model of the environment is required.
- Reinforcement learning works well in distributed systems where the learning approach is based on local observation only.

The reinforcement learning model (Kaelbling et al. 1996; Jiang 2011) is presented in Figure 2.4.

The learning agent interacts with the outside world, which is called the environment. Each time slot *t*, the agent receives the state of the environments $s_t \in S$. Then based on s_t the agent takes an action $a_t \in A(s_t)$, where $A(s_t)$ is the set of available actions for state s_t at time slot *t*. In the next time slot *t+1*, the environment is moved to state s_{t+1} and the agent receives a reward r_t. The agent develops an optimisation policy to maximise the reward at state S.

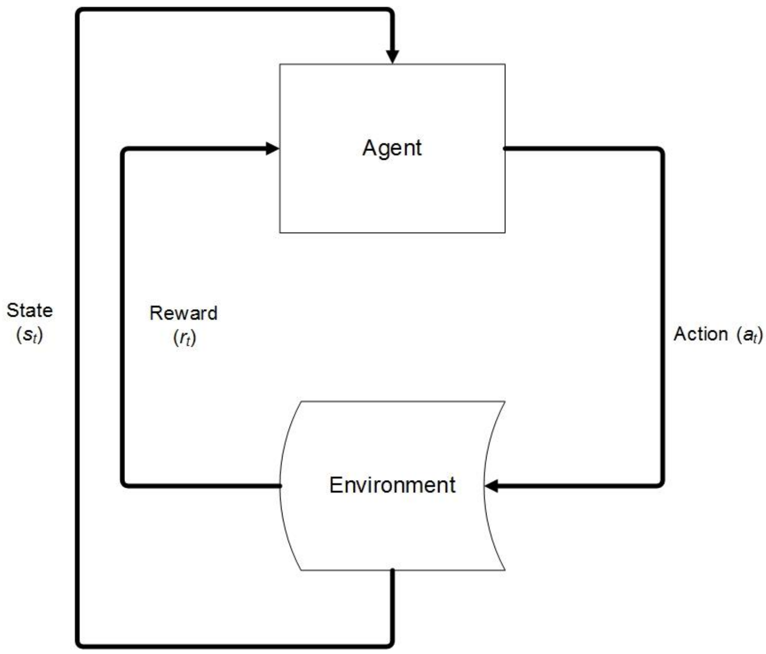

Figure 2-7: Standard reinforcement learning model (Kaelbling et al. 1996; Jiang 2011)

2.8 Fuzzy Interference

Practical networking systems have many complex and dynamic characteristics that involve some uncertainty and result in inaccurate information. The complexity of such systems increases with the number of heterogeneous networking devices that require autonomous and intelligent decision-making abilities. Mathematical models that accurately capture and model all these characteristics and attitudes are either not easily attainable or they are too complicated. Fuzzy logic (Zadeh 1965) provides the necessary mechanism to measure the degree of network parameters in the fuzzy membership functions.

The fuzzy logic concept was introduced by L. A. Zada at the University of California at Berkeley in 1965 (Zadeh 1965) as a method for implementing systems that accept noisy and imprecise inputs in order to improve efficiency and possibly provide design simplicity. Fuzzy logic is a problem-solving control system that is feasible in implementing a simple, embedded microcontroller or even a complex extensive system of different networking systems. In set theory, the classical (non-fuzzy) crisp set assigns the value of either 0 or 1 in the universal set. Thus, the membership function μ of input in the set A maps any value $x \epsilon A$ to one in the crisp set [0, 1]. The following equation illustrates the membership function of the crisp set:

$$\mu A: x \rightarrow [0,1], \qquad (2.5)$$

where x either belongs to the membership function and has value 1 or does not belong to the membership and has value 0. Fuzzy logic is used to generalise the membership function of the crisp set by considering the values between 0 and 1. It maps the input value to the names and degrees of membership functions. Each membership function introduces a curve that represents the possible degrees for each input value; this process is known as fuzzification. The same value could simultaneously have a degree of more than one membership functions. For example, the load on a wireless network could have a degree of low-load equal to 0.1 and a degree of high-load equal to 0.9. Figure 2.8 shows some examples of commonly used fuzzy membership functions.

The next typical block in the fuzzy model is the rules base. The fuzzy rules consist of two parts that formulate the conditional statement of fuzzy logic. The “IF” part, which is known as *the antecedent* or promise, involves fuzzifying the input and applying the necessary fuzzy operator to obtain a fuzzy set value between 0 and 1. The “THEN” part consists of the *consequent* or conclusion, which results in an entire fuzzy set that is then defuzzified to obtain crisp output value. General linguistic IF-THEN statements are shown in the following equation:

$$IF < \text{antecedent} > \; then < \text{consequent} >. \tag{2.6}$$

There are two major implementations of fuzzy inference systems: the Mamdani (Mamdani 1974) inference system and Takagi-Sugeno (Takagi and Sugeno 1985) fuzzy reasoners. In this study, the Mamdani inference system is used because it is intuitive and it is widely accepted.

The Mamdani inference system is composed of the following blocks:

- The fuzzification process maps the crisp values into a fuzzy set using predefined membership functions;

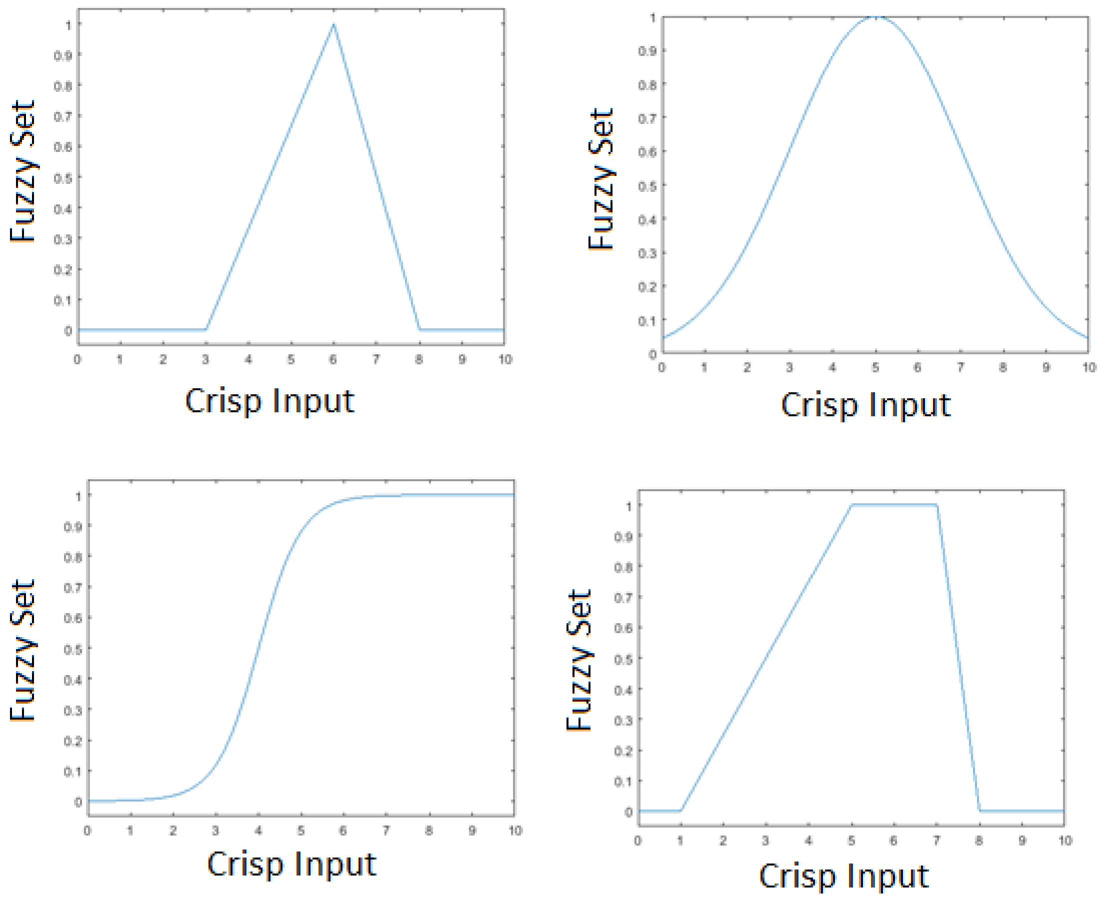

Figure 2-8: Various shapes of commonly used membership functions.

- The set of rules and the strength of each rule are defined based on the fuzzy input set;
- The fuzzified values are employed to evaluate the rules base to obtain the output fuzzy set; and
- The output fuzzy set is defuzzified to obtain a crisp value.

The fuzzy rules utilise the concept of “and”, “or” and sometimes “not “operator. Although there are many ways to compute the “and” operator in a fuzzy set, the most common is the following:

$$Min(\mu A(x), \mu B(x)), \tag{2.7}$$

where *μA* is the membership function of fuzzy set *A* and *μB* is the membership function of the fuzzy set. This technique is known as Zadeh, which is the name of its inventor (Zadeh 1965). Like the fuzzy operator "and", the "or" operator has many definitions, the most common of which is the Zadeh definition shown in the equation below:

$$Max(\mu A(x), \mu B(x)). \tag{2.8}$$

The final step is defuzzification, which is the process of mapping the output fuzzy set to a crisp value. The most commonly used method is the centroid or centre of gravity, which was developed by Sugeno in 1985. The only problem with this approach is that it is computationally difficult for complex membership functions. However, in this research, the membership functions have a simple trapezoid shape. Hence, the centroid defuzzification is calculated using the following equation:

$$Crispoutput = \frac{\int \mu C(x) x dx}{\int \mu C(x) dx}, \tag{2.9}$$

where *Crisp output* is the defuzzified value of the output fuzzy set, and *μ* is the aggregated membership function for the output fuzzy set *C*. Figure 2.6 shows an example of Mamdani rules used in the centroid defuzzification method.

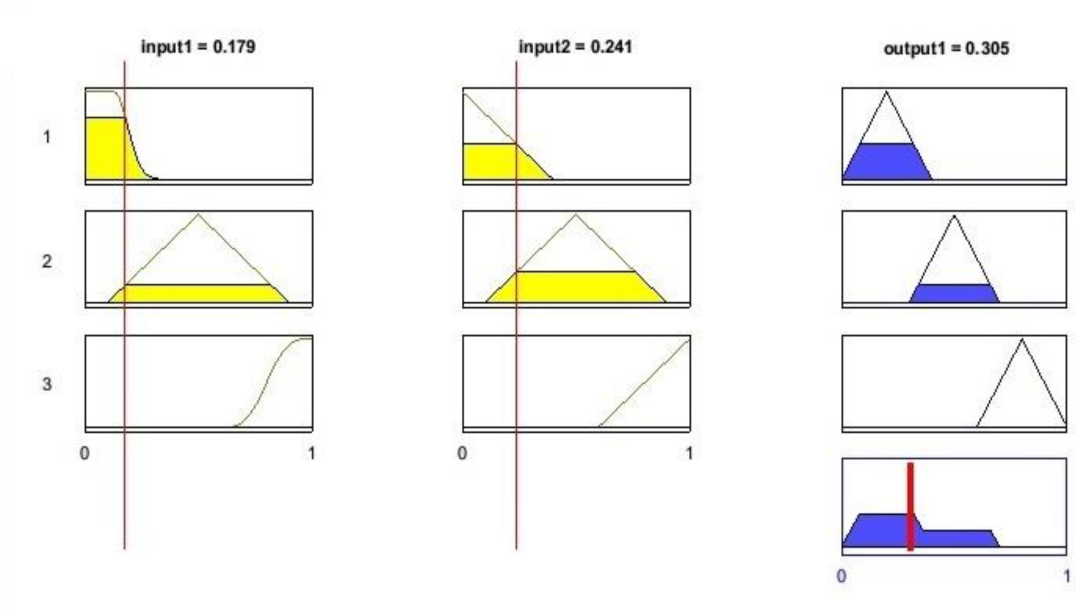

Figure 2-9: The two inputs, two rules Mamdani fuzzy inference system with a centroid defuzzification result.

2.9 Summary

This chapter has provided a review of the state of the art literature related to the research presented in this thesis. The review revealed that the transmission rate of IEEE 802.11 is an essential link characteristic of wireless local area networks. IEEE 802.11 supports multiple transmission rates, and for each rate, there is a different transmission and interference range. The advanced rate adaptation algorithms were developed for infrastructure-based wireless networks. Because of the nature of WMNs, in which wireless nodes compete to access shared channels, it is not easy to adapt existing rate adaptation algorithms.

The review indicated that combining different wireless technologies, such as LTE and WMN is a key opportunity for developing future wireless networks. Although these wireless networks have been used in many communication systems, the research on their integrated use is still limited. The use of heterogeneous networks in existing systems does not manage the heterogeneous radio access technologies as a part of a single virtual network, which does not optimise the bandwidth of each network. The design of heterogeneous systems is highly complex because of the high diversity of associated devices and resources, as well as the increasingly dynamic formation of networks.

A potential method for simplifying the complexity of wireless networks is to use the cognitive networks paradigm. In cognitive networks, a general issue is finding the actions that move the network from a current situation to a desired situation, which tends to be a non-deterministic polynomial-time (NP) -hard problem. The problem that a cognitive network model faces in heterogeneous WMNs is challenging because of the need to secure the quality of service (QoS) characteristics of multiple network architectures and to find the optimal solution using reasoning mechanisms.

The advances in semantic reasoning and ontologies provide an opportunity to overcome the limitations of cognitive network systems. Semantic technologies employ an external knowledge base that provides a mechanism for representing different wireless networks and creating relationships between heterogeneous network characteristics.

In the context of managing wireless networks, semantic reasoning based on ontologies has shown significant enhancement in advertising network services and managing wireless networks. However, the review of the literature revealed a gap in the use of ontologies and semantic reasoning in representing parameters in cross layers of the network protocol stack to manage and optimise heterogeneous wireless networks.

The cognitive network model employs AI mechanisms to simplify the complexity of managing modern wireless networks and to enhance network performance.

Reinforcement learning and fuzzy inference have been shown to enhance wireless networks significantly.

Standard management systems and optimising algorithms in wireless networks have been utilised in the past to manage single network architecture or to switch transmission from one network to another either to offload a congested network or to avoid bad channels. A new network architecture is required to utilise the available non-overlapped frequency band in the different heterogeneous networks as a single virtual network and to optimise the performance of the resulting system using the parameters of different architectures and cross layers in the network protocol stack.

Chapter 3

Cognitive Network Framework and System Modelling

This chapter introduces and discusses the cognitive network framework proposed in this study. The main novelty of the new framework is its provision of a basis for building an intelligent framework that captures network parameters and represents the fundamental relationships among different wireless devices, which can be understood by machines. The proposed framework employs ontologies and reasoning to establish an abstraction model of the various heterogeneous wireless devices. This model enhances the interoperability and integration of different and complex communication and networking systems by enabling reasoning, classification and other types of assurance and automation. This chapter is organised as follows: section 3.1 introduces the cognitive network framework, section 3.2 defines the modelling system employed in this research and section 3.3 summarises the chapter.

3.1 Cognitive Network Framework

For the purpose of this research, the proposed cognitive network framework is defined as an intelligent system that collects QoS parameters from different layers in the network protocol stack and establishes an interface between different wireless network architectures. In other words, this framework facilitates the process of using, managing, and combining different wireless network architectures by separating the heterogeneous networks infrastructure from the control system. It establishes an extendable, smart middleware that automatically manages, configures and optimises the performance of various networks. Figure 3.1 shows a block diagram of the proposed cognitive framework, which has three main parts: QoS metrics management system, heterogeneous network management system and a routing decision-making system.

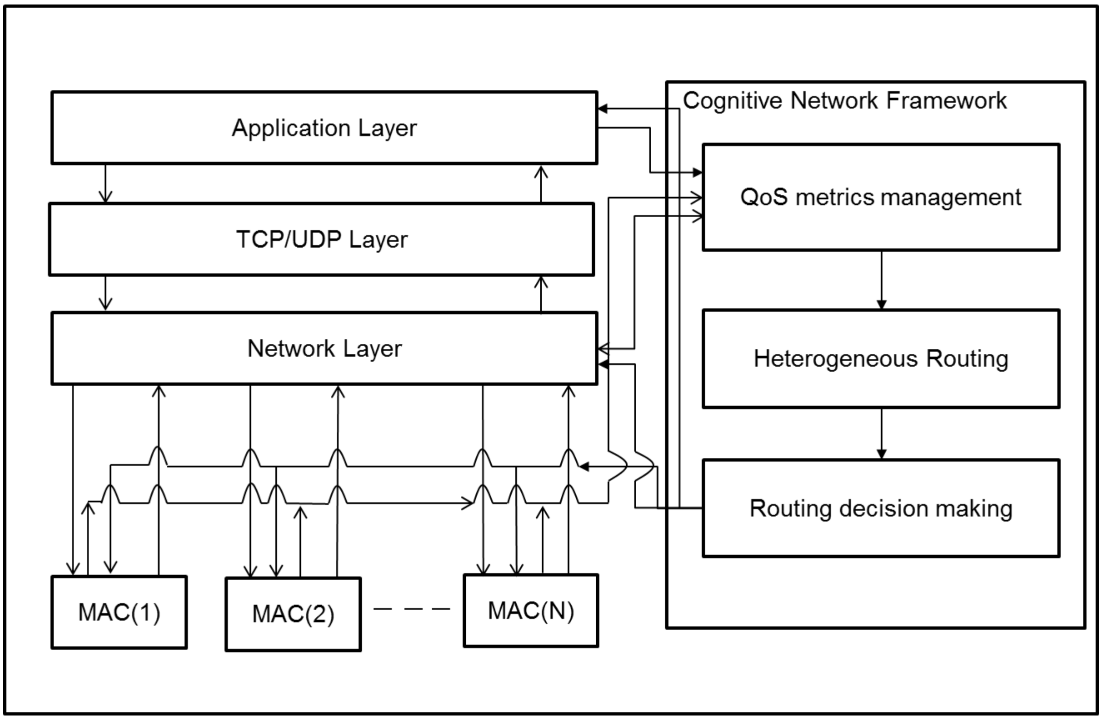

Figure 3-1: Cognitive network framework

Figure 3.2 provides a detailed description of the cognitive framework parts. The QoS management system provides a shared boundary between the proposed framework and the network protocol stack, which represents the different layers of the computer networking system that are shown in Figure 3.1. The QoS metrics management system obtains node configuration parameters and various network characteristics, such as load, quality of the communication channel, resource block (RB), channel quality indicator (CQI) and the transmission rate of the Wi-Fi device (a new rate adaptation algorithm is proposed in Chapter 4). This framework controls the transmission rate on WMN and optimises the use of RB in the LTE network. The heterogeneous network management system manages the process of exchanging information between neighbouring nodes using different network architectures. It introduces a new heterogeneous network architecture and a heterogeneous routing protocol that prescribes the process of exchanging the required information between the neighbouring nodes of different network architectures, which is described in Chapter 5. The third part is the decision-making system, which obtains the input parameters from the heterogeneous routing system and performs the process required to send the decision to the corresponding layer of the network protocol stack. This part of the framework is implemented using two novel approaches. The decision system is first implemented using cross layers of QoS parameters from each network type, and a reinforcement learning algorithm is developed to select the transmission technology in heterogeneous network; this part is described in Chapter 5. The second approach introduces a semantic decision system that uses ontologies and a fuzzy reasoner to manage and optimise the heterogeneous networks and facilitate the dynamic addition of new network types. Figure 3.2 shows a block diagram of this approach.

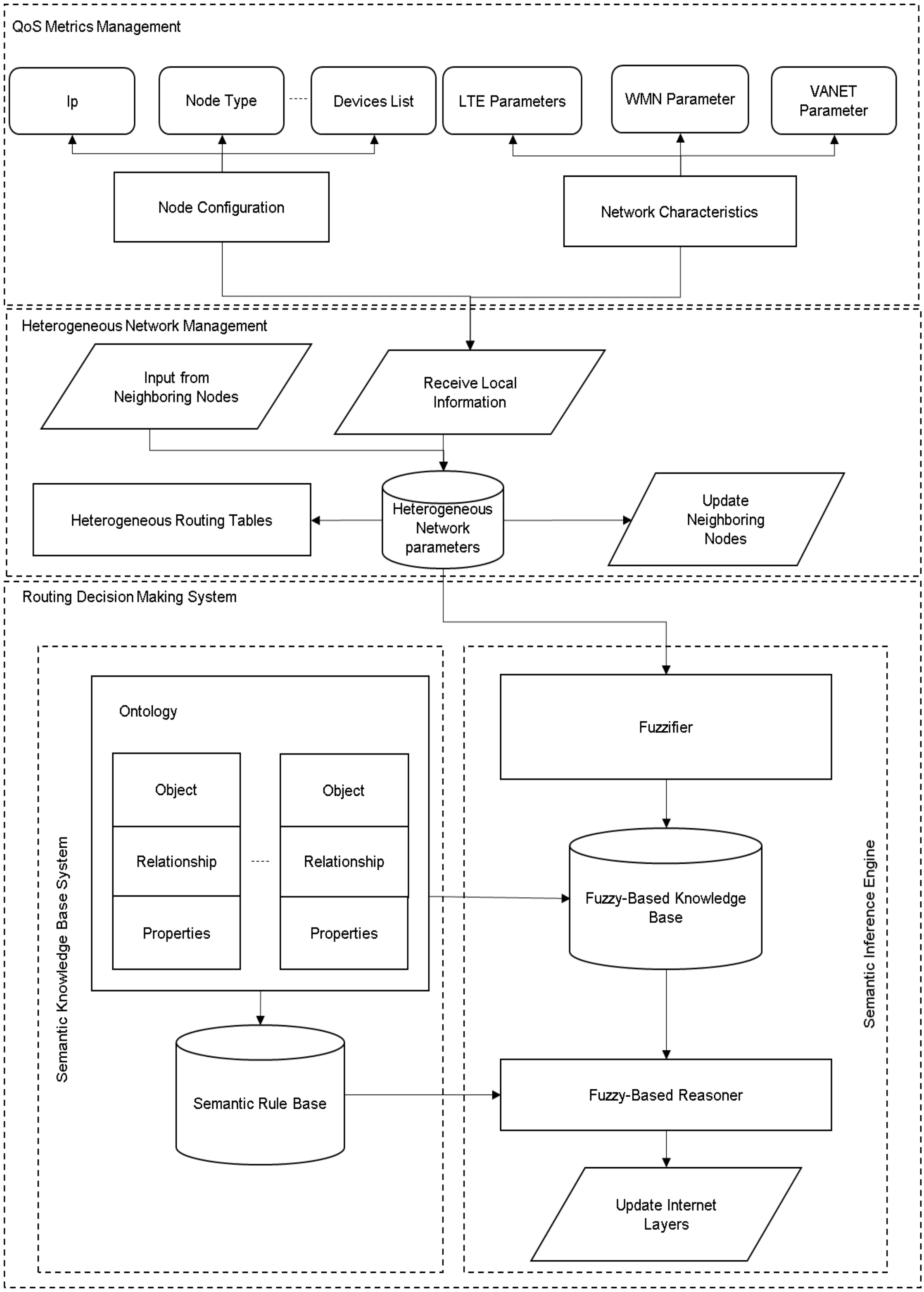

Figure 3-2: Detailed description of the cognitive framework.

The QoS parameters are received from different layers of the network protocol stack. The fuzzification process then converts these values into fuzzy sets and stores them in a fuzzy knowledge base using ontology classes and properties. The reasoner and rule base use the data in the fuzzy knowledge base to perform actions on the network, such as changing the transmission rate of Wi-Fi device in MAC layer, through sending them to the network layers.

The routing decision-making system uses, manages and adds different wireless network architectures. It consists of a semantic knowledge base that uses the ontology and rule base to optimise and control the heterogeneous wireless network, in addition to a semantic inference engine that uses a fuzzy-based reasoner to infer a set of actions to optimise the heterogeneous network. During the functioning of the cognitive network framework, the QoS metrics management system collects local parameters from the network protocol stack and passes these data to the heterogeneous network management system. The heterogeneous network management system stores the local parameters and the data obtained from the neighbouring nodes in a database. A fuzzifier system then processes the data in this database to obtain the fuzzy set of heterogeneous network parameters, which are stored as instances of the ontology classes and properties in the fuzzy-based knowledge base. A fuzzy-based reasoner then uses the instances of the ontology in the knowledge base and the set of rules in the rule base to infer the next actions in the heterogeneous wireless network and to select the network architecture that can handle the transmission. This fuzzy-based reasoner is based on the Mamdani reasoner (Mamdani 1974). A centroid method, or centre of gravity, of defuzzification is used in this phase. The reasoner then sends the decision to the layer in the IP stack that is responsible for performing the required action. The semantic knowledge base system, semantic inference and fuzzy-based reasoner are explained in Chapter 6.

3.2 System Modelling

In this research, simulation is utilised to validate and evaluate the different types of wireless networks and communication systems. Shannon (1998) defined simulation as "the process of designing a model of a real system and conducting experiments with this model for the purpose of understanding the behaviour of the system and /or evaluating various strategies for the operation of the system". Simulation tools allow the modelling of complex systems in detail.

In this work, a computer network simulation tool is employed, which is an event-driven simulation. This type of simulation tool is utilised to model computing devices that are connected by communication links. The communication devices are usually based on random actions. For example, if the radio access network detects a collision, it waits for a random time before it starts the retransmission process. Computer network simulators are employed to provide a modelling application program interface (API), data analysis capabilities, libraries of various network models and standard protocols to support the task of modelling and experimenting modern complex networks. The many examples of network simulators include the Network Simulator 2 (ns-2) (ns-2 n.d.), Network Simulator 3 (ns-3) (ns-3 n.d.), QualNet (QualNet n.d.), OMNeT++ (OMNETST n.d.), SSFNet (Renesys n.d.), NetSim (TETCOS n.d.) and the OPNET Modeller (Riverbed n.d.).

In this work, ns-3 is employed to model and validate the research. The reason that this simulator was selected is that it has a modular architecture, and it supports a broad range of network types, such as ad hoc, mesh network, vehicular networks, Wi-Max and LTE.

The ns-3 simulator allows researchers to perform systems that are complex or not easy to conduct in the real world. The simulator allows researchers to analyse network performance in a very controlled and reproducible environment. The simulator is used to show the function of IPs and networks. In brief, the simulator is used to introduce a model that describes the work and the performance of data networks and creates a simulation engine that can be used to conduct simulation experiments.

The ns-3 simulator is open-source software that provides the ability to extend the existing modules to support more functionalities. It is used by a wide community of researchers worldwide because of its many features and the large number of various wired and wireless networks included in the simulator. The ns-3 is an object-oriented simulator, and is mainly written in C++ and Python.

In this research, the ns-3 was selected as the simulation tool because of its design. The ns-3 was developed as a set of libraries that can be combined with external libraries to establish a complex system that can be analysed carefully. This work utilises three different types of network models in ns-3. The first network type is WMNs, in which ns-3 implements various routing protocols for the network layer and provides the specifications for the medium access layer and multiple physical implementations including IEEE 802.11 a, b, g, and n. The second network type is the vehicular ad hoc network (VANET), which the simulator implements as an approved amendment to the IEEE 802.11 standard to add wireless access in vehicular environments (WAVE). The third type of network architecture that this work utilises is long-term evolution (LTE). In this research, the LTE-EPC network simulator (LENA) (Baldo et al. 2011) is used to build the LTE network. LENA is an open-source LTE network modular system that was based on ns-3 to implement the Internet system. LENA allows researchers to build LTE networks with small and macro cells, and it evaluates network performance, radio resource management algorithms, inter-cell interference coordination solutions, load balancing, mobility management, heterogeneous network (HetNets) solutions and cognitive LTE systems. Figure 3.3 shows an overview of the LENA model.

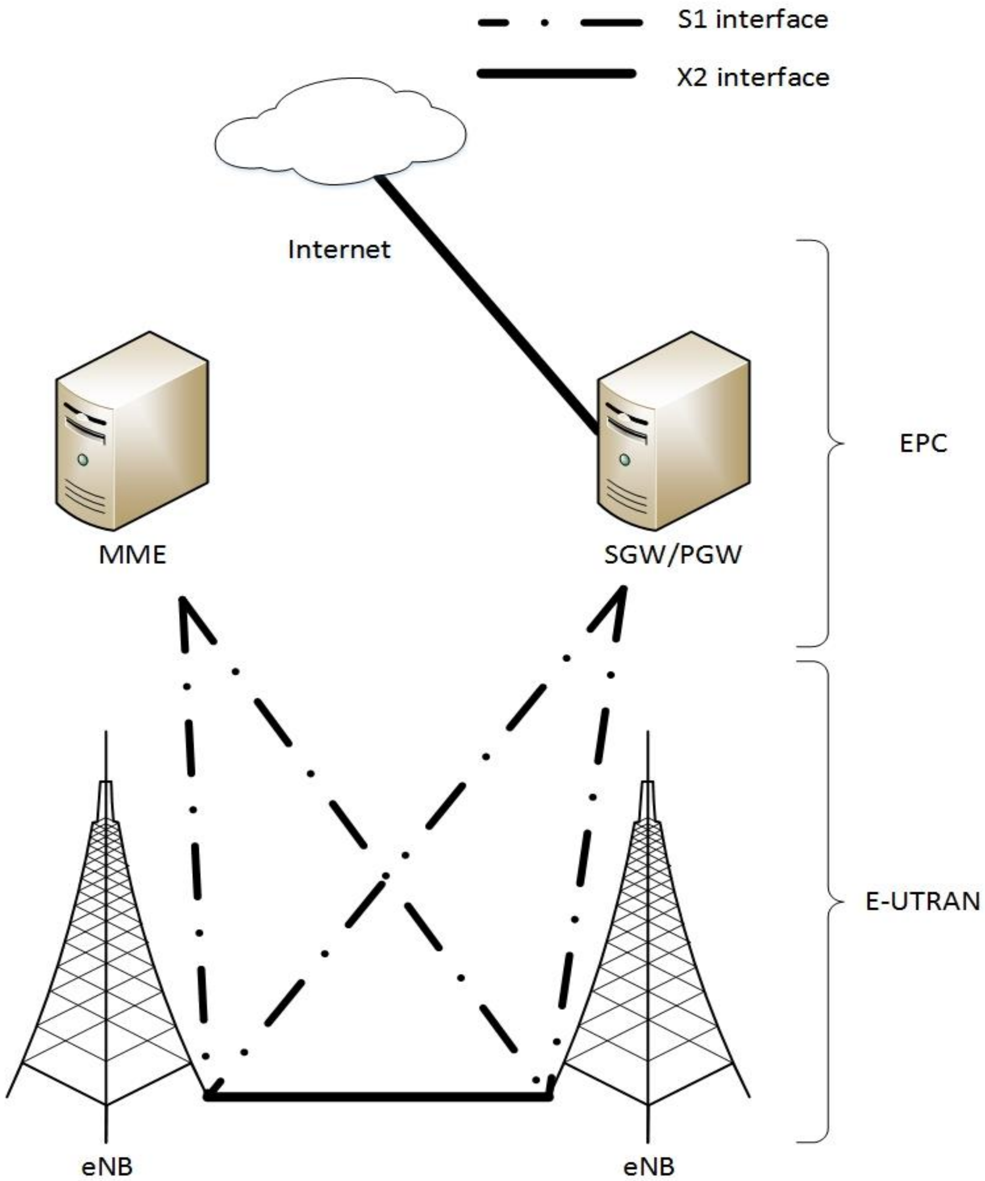

Figure 3-3: Overview of the LENA model (LENA n.d.).

The EPC model in LENA supports the following features:

- Network packets are type IPv4;
- SGW/PGW are implemented in a single node; and
- Multiple eNB node communication are supported over IP networks.

3.3 Summary

This chapter has introduced the new cognitive network framework that works as an adaptor to heterogeneous transmission technologies and enables the interaction and management of various network architectures. It facilitates integration among heterogeneous network architectures that employ different radio access networks by creating relationships among technology-dependent parameters and storing them as an instance of heterogeneous network ontology in a knowledge base. The proposed framework could be used to develop different services through the use of an inference engine by adding new rules for reasoning based on the knowledge base and the ontology. The ontology determines the relationships between technology-dependent parameters in the network protocol stack and enables, through the use of inferences, the utilisation of the observed data from the network. The proposed model provides the foundation for further exploration of the use of semantic technologies in representing various wireless transmission technologies to support nodes with limited resources and in developing smart and self-configured network applications for the next-generation networks, such as smart homes and smart cities.

Chapter 4

Multi-Rate Medium Access Protocol Based on Reinforcement Learning

This chapter introduces a new QoS parameter for estimating the channel and link quality of wireless nodes that utilise Wi-Fi networks. The novelty of this approach is described by considering the characteristics of wireless mesh networks in which the channel condition of neighbouring nodes is used to calculate the transmission rate. A new reinforcement learning algorithm is developed for the rate adaptation algorithm, in which each wireless node selects the transmission rate by learning from previous actions.

This chapter is organised as follows. Section 4.1 introduces the transmission rates in IEEE802.11 and their impact on the wireless networks performance. Section 4.2 introduces the proposed rate adaptation algorithm based on reinforcement learning (RARE). Section 4.3 describes the simulation scenarios and discusses the results obtained from each scenario.

4.1 IEEE 802.11 Transmission Rates

WMNs typically employ IEEE 802.11 to provide a cost-effective approach to indoor and outdoor broadband wireless networks. The IEEE 802.11 standard defines a medium access control (MAC) layer and a physical layer. The MAC is based on carrier-sense multiple access with collision avoidance (CSMA/CA) and a distributed coordination function (DCF). The physical layer employs different modulation and coding techniques, which results in providing multiple transmission rates. By applying a higher transmission rate, the node sends data packets faster, which shortens the required transmission time and increases the throughput. However, to decode the received packets, the power of the signal in the receiver should be higher than a predefined value known as signal-to-interference-to-noise ratio (SINR). SINR is the ratio of the desired signal power to the power of interference and noise. Because of the utilised modulation scheme, a higher transmission rate requires a higher SINR in the receiver in order to decode the packet successfully. Therefore, employing a higher transmission rate requires higher transmission power in order to meet the SINR needed in the receiver, which results in greater interference among other nearby WMN nodes and thus reduces the overall network throughput. The use of different transmission rates results in different coverage ranges that depend on several factors, such as environment, power level and antenna gain. Figure 4.1 shows the different transmission ranges of each transmission rate for IEEE 802.11b (Florwick et al. 2011) in which the higher rate covers a smaller area. For example, the range of a rate of 11 Mbps rate is about 390 feet.

WMNs suffer from high interference among the communicating nodes. Thus, the adaptation of WMN transmission rate can improve network performance by mitigating the severe impact of interference on the network. Moreover, congestion in WMNs, especially in the nodes close to the gateway, is one of the main reasons for reducing the throughput. Thus, controlling the transmission speed of each node could lower the impact of congestion on the network.

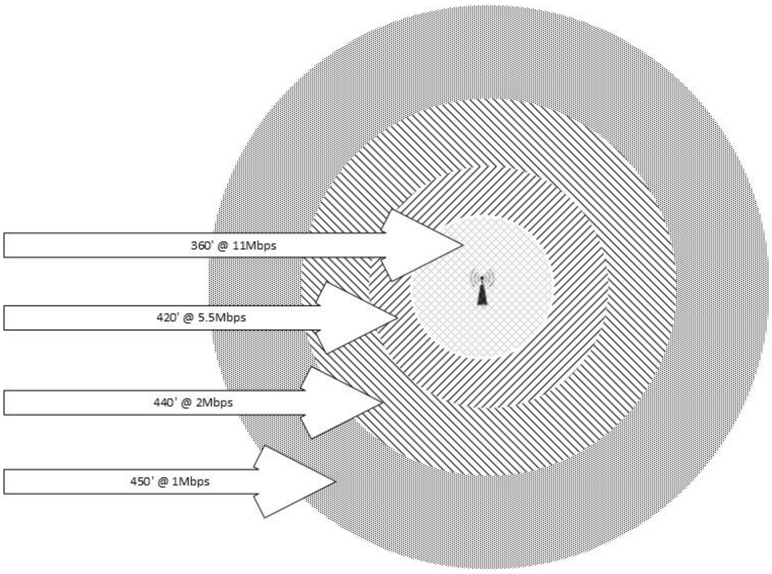

Figure 4-1: Data rate compared with coverage (Florwick et al. 2011).

4.2 Rate Adaptation Based on Reinforcement Learning

In this work, a new reinforcement learning algorithm, named rate adaptation based on reinforcement learning (RARE), is proposed. RARE is an agent-based algorithm where each node acts as an intelligent agent. Each agent calculates the probability of accessing the communication medium based on the number of unsuccessful transmissions and the current transmission rate. In addition, each node receives a “hello” message periodically from its neighbours containing the transmission rate, the probability of accessing the channel and the estimated traffic load. Reinforcement learning is utilised by each node to calculate whether the likelihood of accessing the channel has improved since the last transmission message. Thus, it learns from previous actions whether it is necessary to update the transmission rate. It mitigates the negative impact of updating the transmission rate when the throughput degradation is caused by channel error, not interference. Moreover, each agent estimates the load on its node by calculating the average queue length and then uses this information to decide whether to increase, decrease or keep its transmission rate. The flowchart of *RARE* algorithm is shown in Figure 4.2.

The reinforcement algorithm utilised in this work is based on Q-Learning (WATKINS and Dayan 1992) and the general equation of this learning algorithm is calculated using the following:

$$Q(t_i) = (1-\alpha)Q(t_{i-1}) + \alpha[R(t_i) + \gamma Q(i_{i+1}) - Q(t_{i-1})], \tag{4.1}$$

where α is the learning rate ($0 \le \alpha \le 1$), t_i is the current time, t_{i-1} is the previous time and γ is the discount value. If $\alpha = 0$ then there is no learning in the algorithm; if γ=0 the reinforcement learning is opportunistic, which maximises only the current reward.

The reinforcement learning algorithm consists of two parts, the exploration stage in which the algorithm starts to initialise the parameters used in the algorithm. Then, the learning phase begins by evaluating each action performed by the network nodes.

The algorithm explores the network environment by setting the data rate to the maximum value that the physical device can support. Then, it initialises other parameters to zero as shown in Figure 4.2. In order to estimate the load on each node, equation (4.2) (Senthilkumaran and Sankaranarayanan 2013) is employed to calculate the average queue length.

$$Qlen^d(t_i) = (1-w)Qlen^d(t_{i-1}) + IQ^d(t_i) * w, \tag{4.2}$$

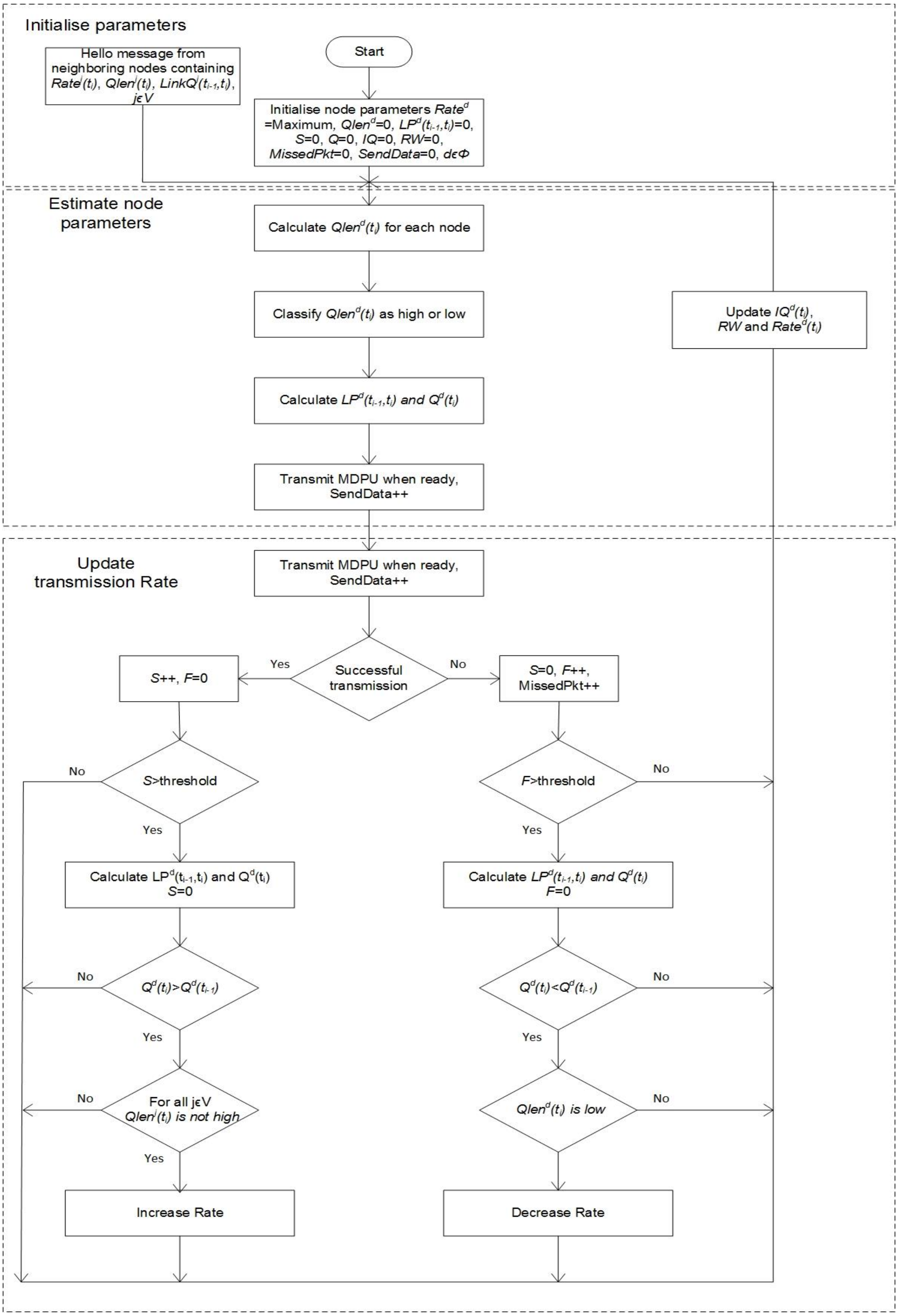

Figure 4-2: RARE flowchart.

where $Qlen^d(t_i)$ is the average queue length of node $d \in \Phi$ and Φ is the set of all available nodes in the network, t_i represents the current time and t_{i-1} is the previous time, $IQ^d(t_i)$ is the queue length at time t_i and w is the queue length weight ($0 \le w \le 1$, $w = 0.5$ is selected empirically). Next, the algorithm classifies the load on the node to either low or high. It employs two thresholds to evaluate whether the node is congested. These are the minimum queue length (*MinQthr*) as shown in equation (4.3) (Senthilkumaran and Sankaranarayanan 2013) and maximum queue threshold (*MaxQthr*) as shown in equation (4.4) (Senthilkumaran and Sankaranarayanan 2013). If $Qlen^d(t_i)$ is below *MinQthr*, the load on the node is assessed as low; if it is above *MaxQthr*, then the load is considered to be high.

$$MinQthr = 0.25 * MaxQL, \tag{4.3}$$

$$MaxQthr = 3 * MinQthr, \tag{4.4}$$

where *MaxQL* is the physical maximum queue length of the Wi-Fi device. *RARE* uses equation (4.1) to maximise the probability of accessing the wireless channel (*LP*) by learning from the previous updates of the transmission rate. The reward function of Q-learning employs both *LP* (Benslimane and Rachedi 2014) and reward weight (*RW*). *RW* is either a positive value, to improve the chance of increasing the transmission rate, or a negative value, to increase the probability of reducing the transmission rate. The values used in the simulations are 0.2 and -0.2. RARE does not consider the future state of the network (γ=0) as the network estimate the probability of accessing the channel based current and previous actions. Equation (4.5) shows how Q-learning (WATKINS and Dayan 1992) is incorporated in the proposed RARE algorithm.

$$Q^d(t_i) = Q^d(t_{i-1}) + \propto [LP^d(t_{i-1}, t_i) + RW - Q^d(t_{i-1})], \quad (4.5)$$

where $Q^d(t_i)$ represents the wireless channel condition at time t_i, α is the learning rate (0.4 is used in the experiments). In order to estimate *LP*, each node calculates failure rate during the time interval t_{i-1} to t_i ($FR^d(t_{i-1}, t_i)$) using equation (4.6) (Benslimane and Rachedi 2014).

$$FR^d(t_{i-1}, t_i) = \frac{MissedPkt^d(t_{i-1}, t_i)}{SendData^d(t_{i-1}, t_i)}, \quad (4.6)$$

where $MissedPkt^d(t_{i-1},t_i)$ is the number of unsuccessful transmissions from t_{i-1} until t_i, a value which is obtained from the MAC layer of the IEEE 802.11 device on wireless node *d* by counting the number of missed acknowledgments for each transmission; and $SendData^d(t_{i-1},t_i)$ is the total number of transmissions for node *d* using Wi-Fi from t_{i-1} to t_i.

Then, equation (4.7) (Benslimane and Rachedi 2014) utilises (4.6) to measure the link quality during the time interval t_{i-1} to t_i ($LQ^d(t_{i-1}, t_i)$). The communication link is shared among a set of nodes that compete to access the channel. Therefore, the calculation of $LQ^d(t_{i-1}, t_i)$ considers *FR* and the current data rate of node *d* ($Rate^d$) of the set of nodes *V* that share the transmission link. $LP^d(t_{i-1}, t_i)$ is computed by equation (4.8) (Benslimane and Rachedi 2014).

$$LQ^d(t_{i-1}, t_i) = \frac{\sum_{j \in V} FR^j(t_{i-1}) * Rate^j(t_i)}{\sum_{j \in V} Rate^j}, \quad (4.7)$$

$$LP^d(t_{i-1}, t_i) = \frac{1 - LQ^d(t_{i-1}, t_i)}{\sum_{j \in V} 1 - LQ^j(t_{i-1}, t_i)}, \quad (4.8)$$

Next, when a MAC protocol data unit (MDPU) is available, the node sends the data through the wireless channel. Then based on whether the transmission fails or not, *RARE* updates the transmission rate in order to reduce the interference on the neighbouring nodes and increase *LP*. In case of a successful transmission, if the number of consecutive successful transmissions (*S*) is higher than a given threshold (3 is selected empirically), then RW is set to a positive value and the status of the wireless channel is recalculated using equation (4.5). If the wireless link shows improvement since the last transmission and the load in the nodes that share the wireless channel is not high, then the transmission rate is increased. Conversely, if the transmission fails, and the number of consecutive transmissions failure (*F*) exceeds a given threshold (4 is selected empirically) then RW is set to a negative value, and $Q(t_i)$ is recalculated using equation (4.5). Then, if the $Q(t_i)$ is smaller than $Q(t_{i-1})$ and the load on the node is low, then RARE decreases the transmission rate.

Finally, *RARE* updates $Qlen^d(t_i)$, $Q^d(t_i)$ and $LP^d(t_i)$ based on the ‘hello’ messages that each node receives periodically, and proceeds with the next available MDPU.

4.3 Performance Evaluation

In this section, the *RARE* algorithm is evaluated using the ns-3 simulator, which is a widely used tool for evaluating and validating wireless networks. The *RARE* algorithm is compared in terms of average throughput with three state-of-the-art algorithms.

4.3.1 Simulation Setup

Table 4.1 shows the network parameters used in the simulation. A realistic grid scenario similar to the configuration used in (Salem and Hubaux 2005; Allen et al. 2012) is utilised to evaluate this work. Figure 4.3 illustrates the scenario employed in this Chapter in which the gateway is in the centre of the network and four different numbers of nodes are utilised during the simulation (8, 16, 24 and 32). Each node has a transmission range set to 100 metres, and a constant bit rate (CBR) transmission is sent to the mesh gateway, which is in the middle of the grid. In order to analyse the performance of RARE, various amounts of transmission load are applied to the network. In addition, various numbers of transmission nodes are employed to transmit simultaneously to the mesh gateway.

4.3.2 **Evaluating and Validating Results**

The performance of the RARE algorithm is compared with three of the most widely cited schemes that are already implemented on many commercial devices. These schemes are the ARF, AARF and ONOE algorithms. An Analysis of Variance (ANOVA) statistical test is utilised to verify that there is a systematic enhancement in the network that causes the throughput improvement. Fisher's Least Significant Difference (LSD) is employed to assess if the proposed *RARE* achieves higher throughput than the other methods. The

Table 4-1: Simulation setup.

Simulation Parameters	**Assigned Value**
Topology	Grid
Number of nodes	32
Propagation	Two ray ground reflection
MAC	802.11b
Transmission range	100 metres
Number of flows	Varies between 3-17
Packet size	500 bytes

Packet generation rate	Varies between 0.5-3.5 Mbps
Topology covered area	1000 X1000 metres
Transmission rates	1, 2, 5.5, 11 Mbps
Mobility	Static (none)

simulations are run using five different scenarios. In each scenario, a different number of nodes (3, 10, 13, 15, and 17 nodes) are randomly selected from different circles in Figure 4.3 to transmit simultaneously toward the gateway and demonstrate how the proposed system reacts to different loads.

In view of the fact that the distance of the mesh node from the gateway has a notable effect on the WMN performance, each scenario is repeated 10 times where the nodes positions are randomly selected in order to show how the proposed system behaves under different node positions. In order to show that the proposed *RARE* algorithm is statistically different from the benchmark algorithms, the Analysis of Variance (ANOVA) statistical test is conducted on the results of each scenario. The ANOVA is a statistical test that compares groups of data and indicates that at least one of the group differs from the rest. Equation (4.9) (Scheffe 1959) is used to determine whether the algorithms are statistically different.

$$F > F_{Crit,} \tag{4.9}$$

where F is the ANOVA test statistic and F_{Crit} is the critical value extracted from the F-distribution table. If F is larger than F_{Crit} then at least one of the compared data is statically different from the rest. Another parameter is P, which is the probability of differences that occur purely by chance; P should be less than 0.05.

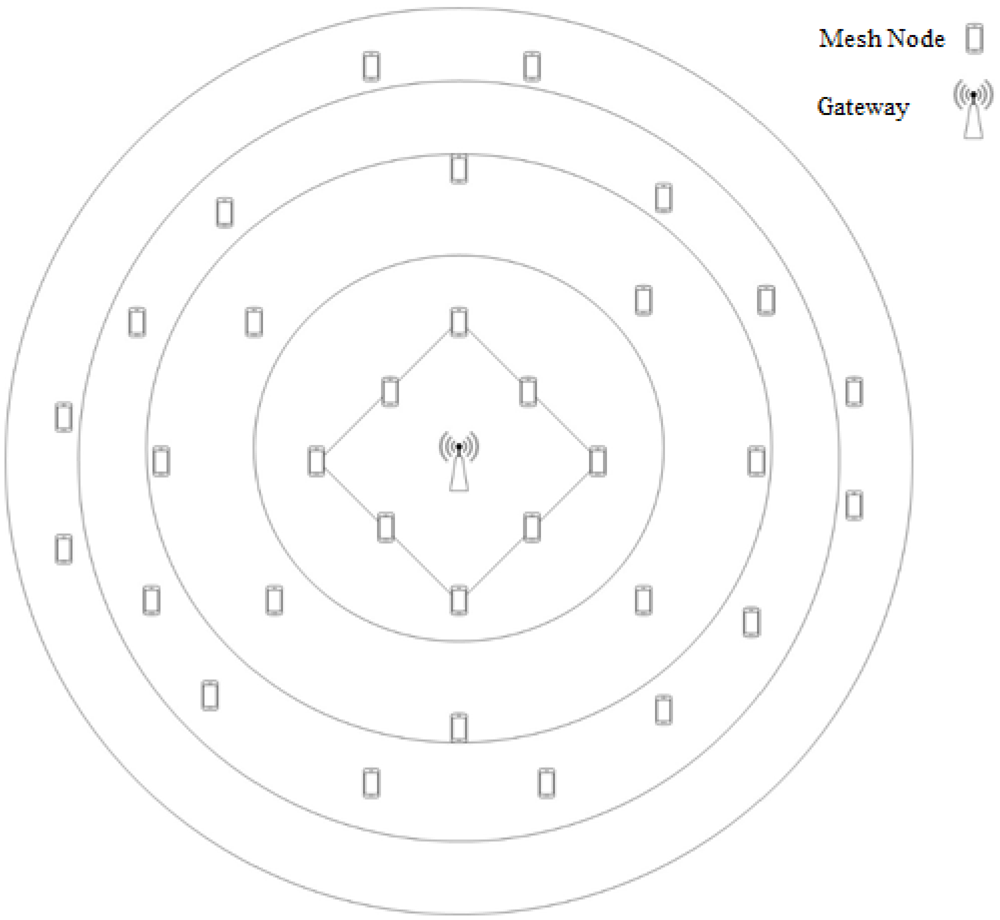

Figure 4-3: Wireless mesh network grid configuration.

Then, in order to check that the proposed algorithm is performing better than the benchmark algorithms, the results from each scenario are submitted to the LSD test. Ten different throughput results are generated in each scenario for each algorithm. The average value of these results is calculated for each algorithm and as the following:

- RAREavr – is the average value of the results for *RARE* algorithm;
- ONOEavr - is the average value of the results for *ONOE* algorithm;
- AARFavr - is the average value of the results for *AARF* algorithm; and
- ARFavr is the average value of the results for *ARF* algorithm;

Then, the different between each average value is calculated using the following(Williams and Abdi 2010) :

$$|\,\text{Avagerage1} - \text{Average2}\,| > \text{LSD} \qquad (4.10)$$

where Average1 and Average2 could be RAREavr, ONOEavr, AARFavr or ARFavr, if the result is higher than the calculated LCD then the two averages are statistically different.

Table 4.2 and 4.3 shows the ANOVA and LSD results for each scenario respectively. Both ANOVA and the LSD tests show that the proposed algorithm significantly improves the average throughput. Table 4.2 shows two important results, namely, the *F* values for all the scenarios are larger F_{Crit} which indicates that the throughput results are statically different. Secondly, the results are not obtained by chance as the *P values are* smaller than 0.05*.* Then, Table 4.3 shows the LSD results which proves that the throughput results are statically different using equation (4.10). For instance, the average throughput results of the scenario with 10 nodes transmitting are 2344 and 1230.1 for *RARE* and ONOE respectively, while the LSD value for this situation is 809.02. The performance of *RARE* algorithm is significantly higher than *ONOE* because the different between the average results is greater than the LSD.

Figures 4.3, 4.4, 4.5, 4.6 and 4.7 show the average throughput for each algorithm in five scenarios; the results are represented by a box and whisker graph in which the lower box represents the average throughput quartile lower than the median and the upper box represents the average throughputs higher than the median. The upper and lower whiskers represent the highest and lowest value of the results, respectively. For example, Figure 4.5 shows that 50% of the throughput results for RARE are between

Table 4-2: ANOVA test results.

Number Transmission Nodes	ANOVA Test			
	F	***F_crit***	***P***	***MSE***
3 nodes	2.98	2.87	0.04	325826.3
10 nodes	5.8	2.87	0.0019	964887.4
13 nodes	4.79	2.87	0.0071	637264.6
15 nodes	8.38	2.87	0.0003	682446
17 nodes	8.8	2.87	0.0002	811294.2

Table 4-3: LCD test results.

Number Transmission Nodes	Throughput Average for the Four Algorithms Compared				LSD	RARE Improvement		
	RARE	***ONOE***	***ARF***	***AARF***		***ONOE***	***ARF***	***AARF***
3 nodes	1489.2	1213.7	896.6	947.5	450.6	275.4	592.5	541.6
10 nodes	2344	1230.1	935.09	869.44	809.0	1113.8	1408.9	1474.5
13 nodes	3453.9	2564.9	2178.5	2264.7	767.5	889.002	1275.5	1189.2
15 nodes	3406	1949.1	1694.7	1830.5	794.3	1456.9	1711.3	1575.5
17 nodes	3267.6	2026.1	1578.7	1221.5	866.0	1241.51	1688.9	2046.1

3300 and 4000 Kbps while the benchmark protocols achieve throughput between 1400 and 2400 Kbps for ONOE, 1300 and 2600 Kbps for AARF and ARF achieves between 110 and 2100 Kbps. *RARE* achieves up to 36% higher throughput when the median of the results is compared. Moreover, the results indicate that *RARE* performs better when the load on the network is high, unlike other rate adaptation algorithms, which suffer from throughput degradation in highly congested networks. Figure 4.3 shows that the proposed rate adaptation algorithm outperforms the benchmarks with about 17% when only three nodes are transmitting while Figure 4.7 indicates that *RARE* algorithm achieves about 90% higher throughput in which 17 nodes are transmitting simultaneously.

Another scenario is presented to demonstrate how the network performs when a different amount of traffic demands is applied to the network. Figure 4.8 shows the average throughput for the network with nine different loads. The results indicate that the proposed rate adaptation algorithm significantly improves the network performance.

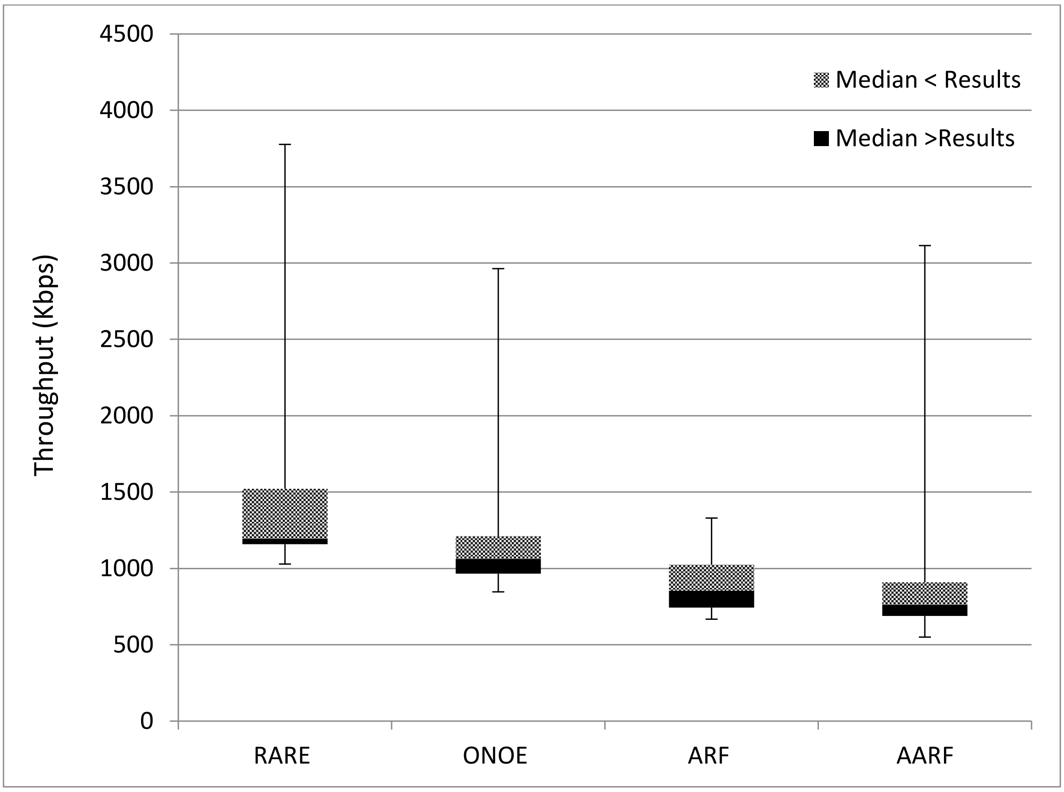

Figure 4-4: Throughput average of 3 nodes transmitting simultaneously.

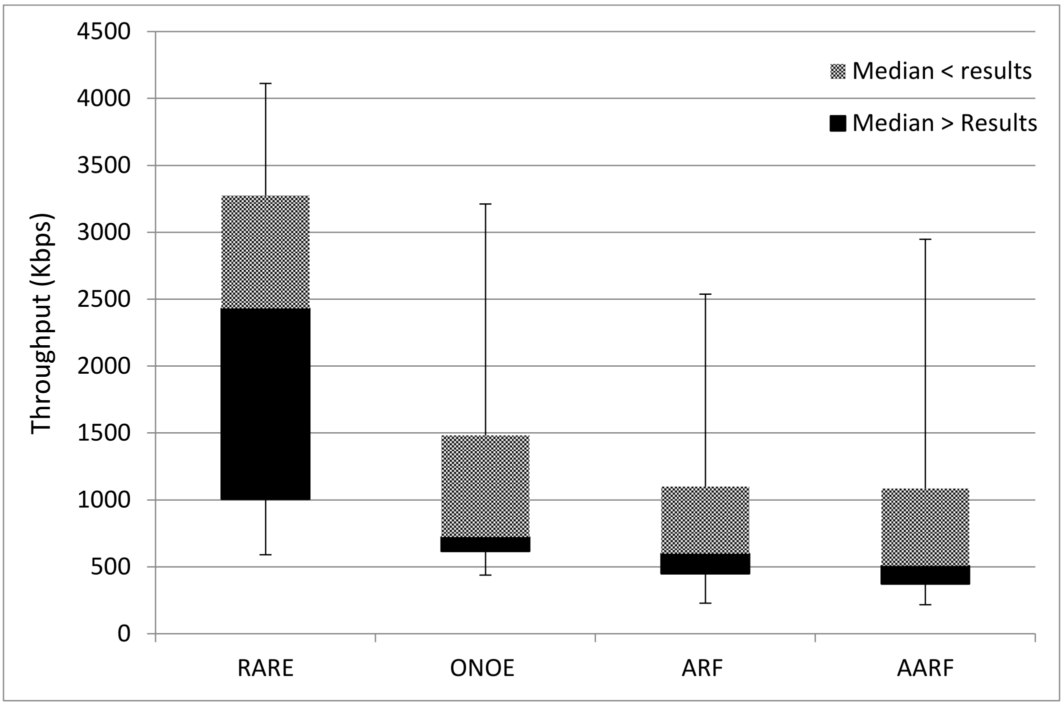

Figure 4-5: Throughput average of 10 nodes transmitting simultaneously.

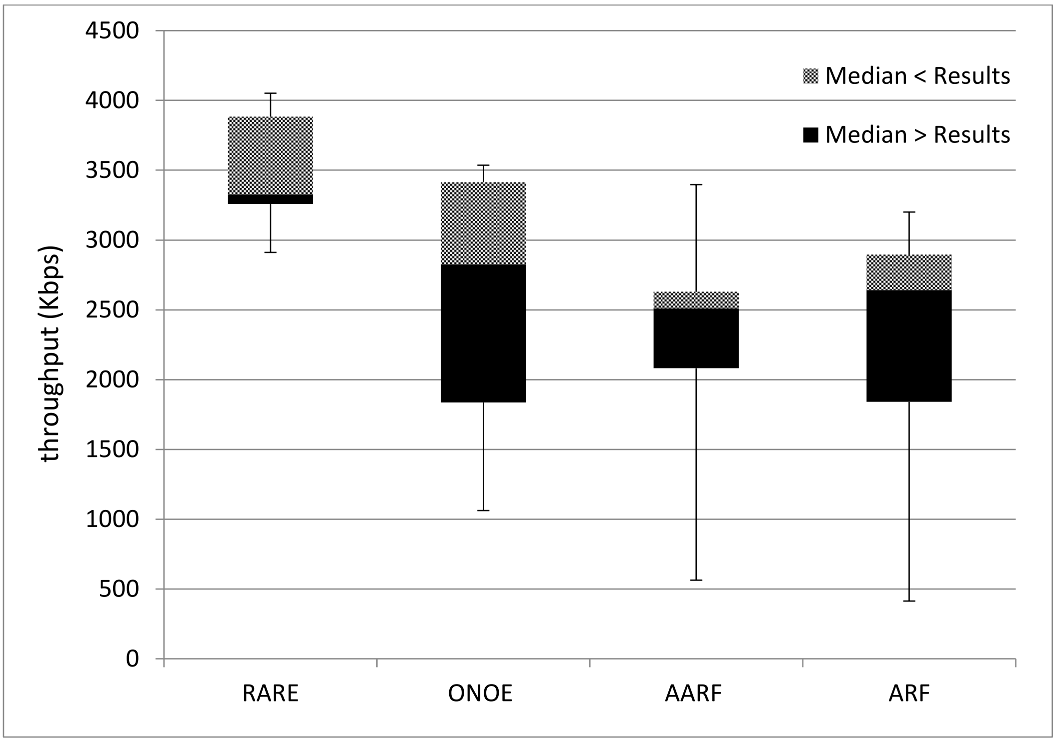

Figure 4-6: Throughput average of 13 nodes transmitting simultaneously.

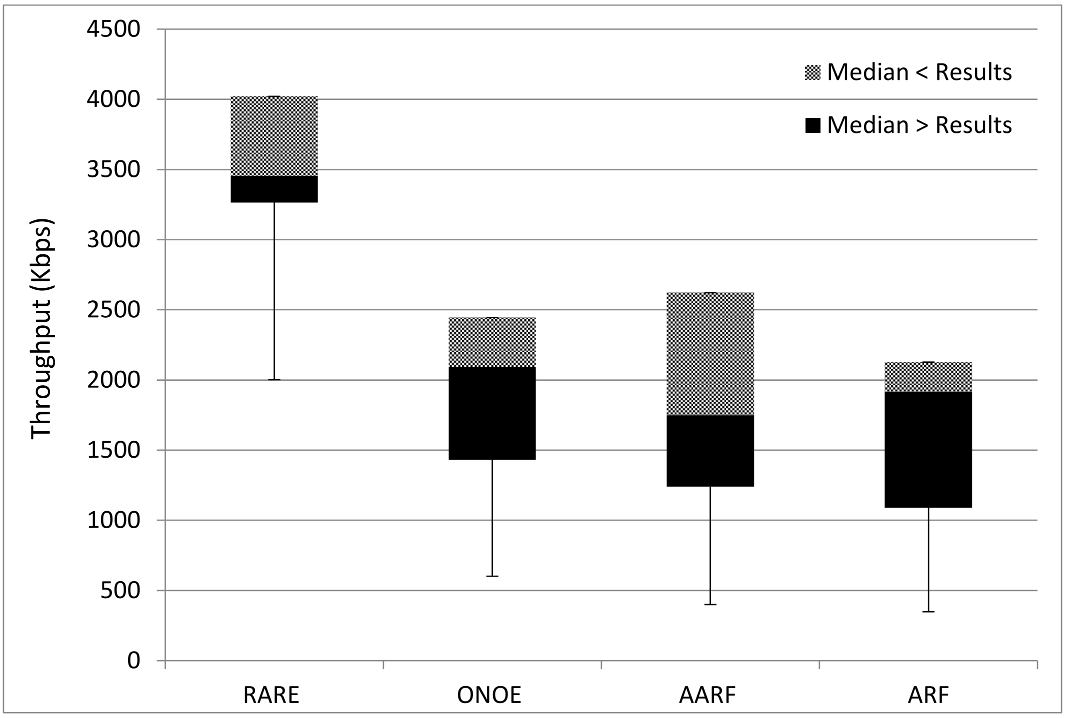

Figure 4-7: Throughput average of 15 nodes transmitting simultaneously.

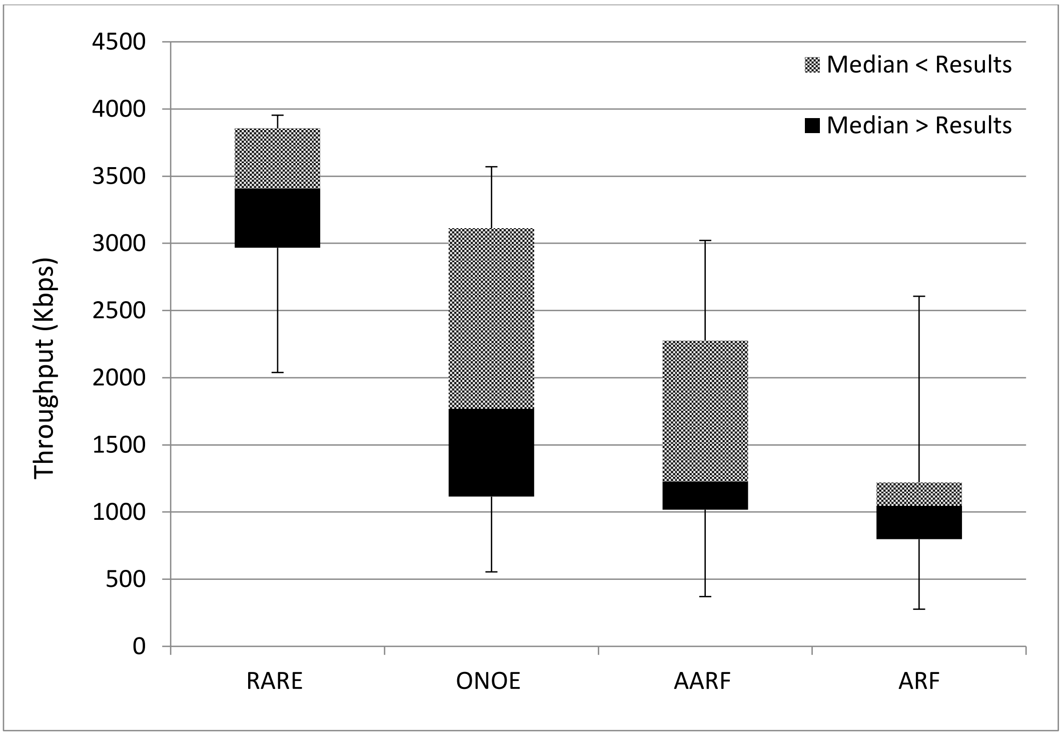

Figure 4-8: Throughput average of 17 nodes transmitting simultaneously.

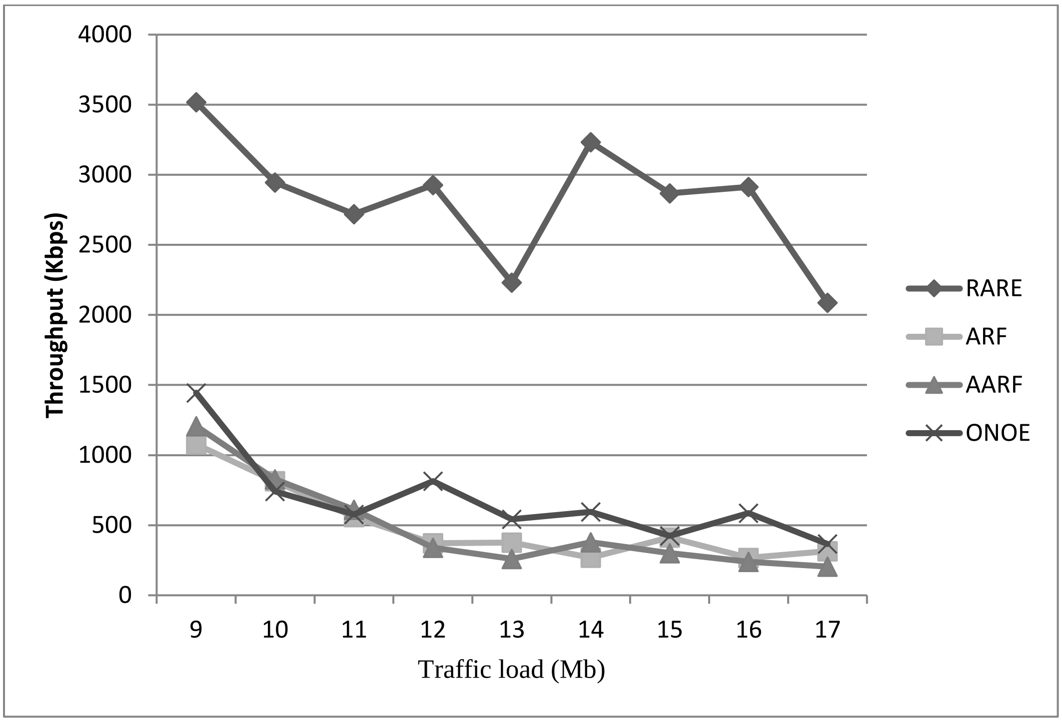

Figure 4-9: Average throughput for network with 9 different loads.

4.4 Summary

This chapter introduced a new reinforcement algorithm that adaptively updates the transmission rate in order to increase the success rate of accessing the channel without interfering with the other nodes in WMN. The algorithm learns from previous updates to avoid unnecessary changes in the transmission rate (e.g., due to channel error rather than interference), which causes packet loss. The proposed algorithm considers the transmission rate of the other nodes that compete to access the transmission channel as well as the traffic load. The simulation results showed that the proposed algorithm achieved higher throughput under different transmission loads and numbers of contending nodes compared with three other state of the art algorithms.

This chapter also introduced a new routing metric that employs the transmission rate of the proposed rate adaptation algorithm to estimate the transmission link quality of WMNs. The proposed rate adaptation algorithm sets the transmission rate based on the link quality of the neighbouring nodes and the load on the Wi-Fi device. Thus, the transmission rate estimates the amount of interference and collision with other nodes and the load on the node. Thus, the best link quality provides the highest transmission rate.

Chapter 5

Heterogeneous Wireless Mesh Networks

This chapter introduces a heterogeneous metropolitan area network architecture that combines an IEEE 802.11 wireless mesh network with a long-term evolution (LTE) network. The proposed heterogeneous network overcomes the problems in sending packets over long paths, island nodes and interference in wireless mesh network. The proposed network increases the overall capacity of the combined network by utilising unlicensed frequency bands of Wi-Fi networks instead of buying additional licensed frequency bands for LTE. The novelty of this network architecture is that its establishes a new architecture derived from various network architectures to create a single network and develop a novel routing protocol that prescribes how the heterogeneous devices communicate with each other.

The Chapter is organised as follows. Section 5.1 introduces the system architecture. Section 5.2 describes the proposed heterogeneous routing protocol, which is then experimentally verified using simulation in section 5.3. Finally, section 5.4 offers summarise the Chapter.

5.1 System Architecture

The proposed heterogeneous wireless mesh network (HetMeshNet) considers the coexistence of multiple wireless technologies as well as a wired network. It employs the following types of nodes:

- NetNodes: The heterogeneous node portion of the WMN that forms the network infrastructure. These nodes are equipped with both Wi-Fi (IEEE 802.11n) and LTE capabilities.
- ClientNodes: The heterogeneous node portion of the WMN that represents the end users and employs Wi-Fi (IEEE 802.11) and LTE capabilities.
- Mesh Gateway: Nodes with Wi-Fi (IEEE 802.11) and wired connections that connect the WMN to the Internet through the Internet Gateway.
- LTE Base Stations: Also known as evolved Node B (eNodeB or eNB).
- Internet Gateway Nodes: Nodes that connect the different networks to the Internet using a high-speed wired network.

Figure 5.1 shows an example of the proposed HetMeshNet architecture. It comprises several types of network components. Firstly, the LTE network consists of a number of cells distributed in the region. An LTE base station is located in each cell. Secondly, a number of NetNodes is deployed in the network, each of which is capable of utilising multiple transmission technologies. The heterogeneous nodes (NetNodes) are equipped

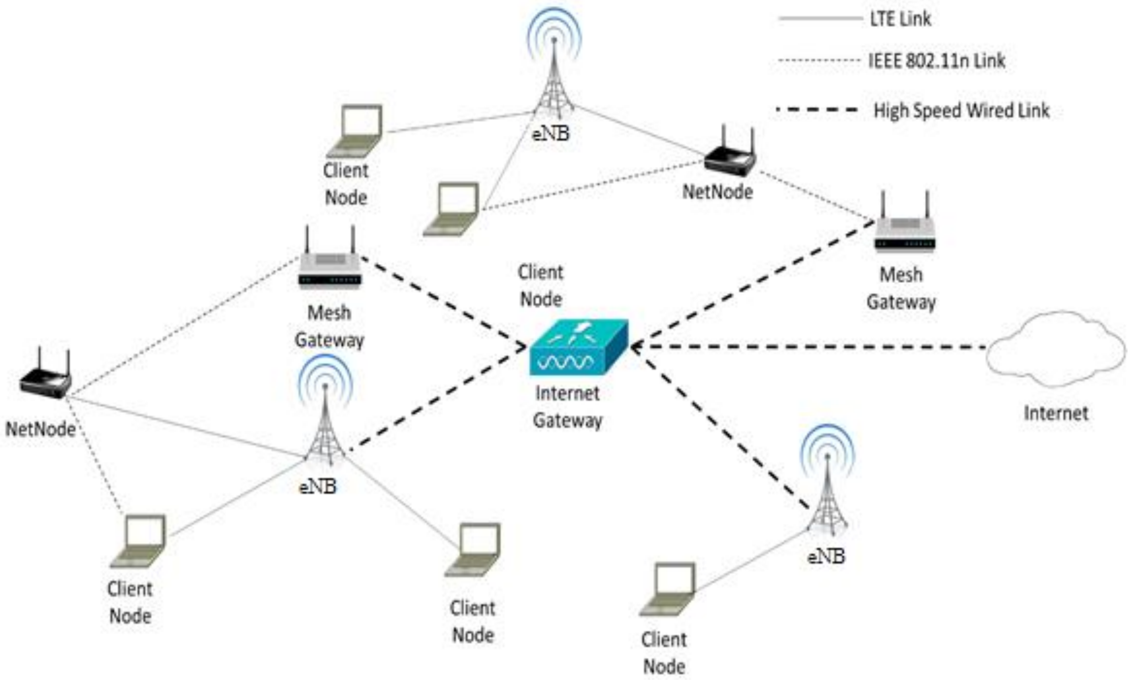

Figure 5-1: Heterogeneous mesh network.

with Wi-Fi and LTE network interface cards. The Mesh Gateway nodes are the third type of nodes, which connect the WMN to the Internet Gateway. The Internet Gateway acts as a server; it provides Internet connection to both the LTE and WMN networks. Finally, the Client Nodes could be a human using a mobile phone, a laptop, or any other device connected to the Internet (e.g., a sensor sending data to the Internet).

Each heterogeneous node in this architecture transmits data to the Internet using either Wi-Fi or LTE. For example, if a NetNode sends the packet to a neighbouring node via Wi-Fi, the neighbouring node forwards the packet using LTE or Wi-Fi. Thus, both technologies are employed to mitigate the disadvantages of each technology, including overloaded nodes or poor-quality wireless channels. By contrast, if a node receives packets from the Internet (downlink), the Internet Gateway decides whether to forward data via LTE or WMN. Note that in contrast to uplink, if Wi-Fi is selected for the downlink transmission, the intermediate nodes cannot switch back to LTE because the intermediate nodes could use a LTE network to transmit to the eNB base station (uplink only).

In this chapter, an urban hotspot scenario is considered, such as a crowded city centre, in which many users wish to access the Internet simultaneously. No interference is assumed among the networks because different frequency bands are employed by the wireless networks. Each cell in the network employs the same architecture, as shown in Figure 5.1. Therefore, this work is focused on a single cell in the LTE network.

5.2 Heterogeneous Routing Protocol

The proposed routing protocol employs metrics from both networks to switch dynamically between transmission technologies. The proposed protocol consists of two main components: the heterogeneous routing tables and a routing algorithm. In a heterogeneous wireless network, the routing protocols need to employ metrics from all the technologies that might be utilised by a node.

5.2.1 Heterogeneous Routing Tables

Each type of node uses different transmission technologies and each transmission technology employs a different network address. In order to route packets between these different networks, each type of node maintains a routing table to forward data packets from different networks just as if they were coming from the same network. Firstly, the Internet Gateway node needs a routing table in order to forward data packets to and from the Internet for both WMN and LTE networks. Secondly, each heterogeneous node maintains a table of routes to the other heterogeneous nodes in the network as well as a list of available Mesh Gateways and the default Mesh Gateway to forward heterogeneous node data. In order to create the routing table, an OLSR routing protocol (Jacquet et al. 2001) is utilised to determine the route table for the Wi-Fi mesh network and employ the hop count as a metric. OLSR is a proactive routing protocol that, based on the hop count metric, selects the route from source to destination. An extension to the OLSR is then added to support the use of the mesh gateway in the WMN. The extended OLSR employs two metrics to select the Mesh Gateway: the number of hops to the Mesh Gateway and the number of nodes connected to it. In order to achieve this, a control message is transmitted to the neighbouring nodes from each Mesh Gateway to advertise its load in terms of the number of nodes associated with it. Each node selects the Mesh Gateway with the shortest path and if more than one Mesh Gateway has the same number of hops, then the node selects the Mesh Gateway with lower load. The use of shortest path to select the route to Mesh Gateway using OLSR will avoid the occurrence of the routing loops and route oscillations problem. Another route table is used in the Mesh Gateway that lists the addresses of the heterogeneous nodes associated with it. Figure 5.2 shows the flowchart of creating the routing tables for each type of node.

The flowchart starts by checking the node type and then a set of control messages are exchanged to maintain the routing table on each node. In the case of a client node with either LTE and Wi-Fi devices or NetNode, OLSR is employed to create a routing table for the WMN; then, it selects the default Mesh Gateway based on two parameters: the distance to the Mesh Gateway in terms of hop counts and the number of heterogeneous nodes associated with the Mesh Gateway.

Wi-Fi devices in client nodes or NetNodes send control messages to the Internet Gateway that piggyback the node IP address of the Wi-Fi network and the LTE network using the LTE transmission technology to transmit the control message to the Internet Gateway through LTE eNB base station. The Internet Gateway employs this information to create a table of the Wi-Fi IP addresses and the corresponding LTE IP addresses. This table enables the Internet Gateway to forward Wi-Fi packets using the LTE network and vice versa.

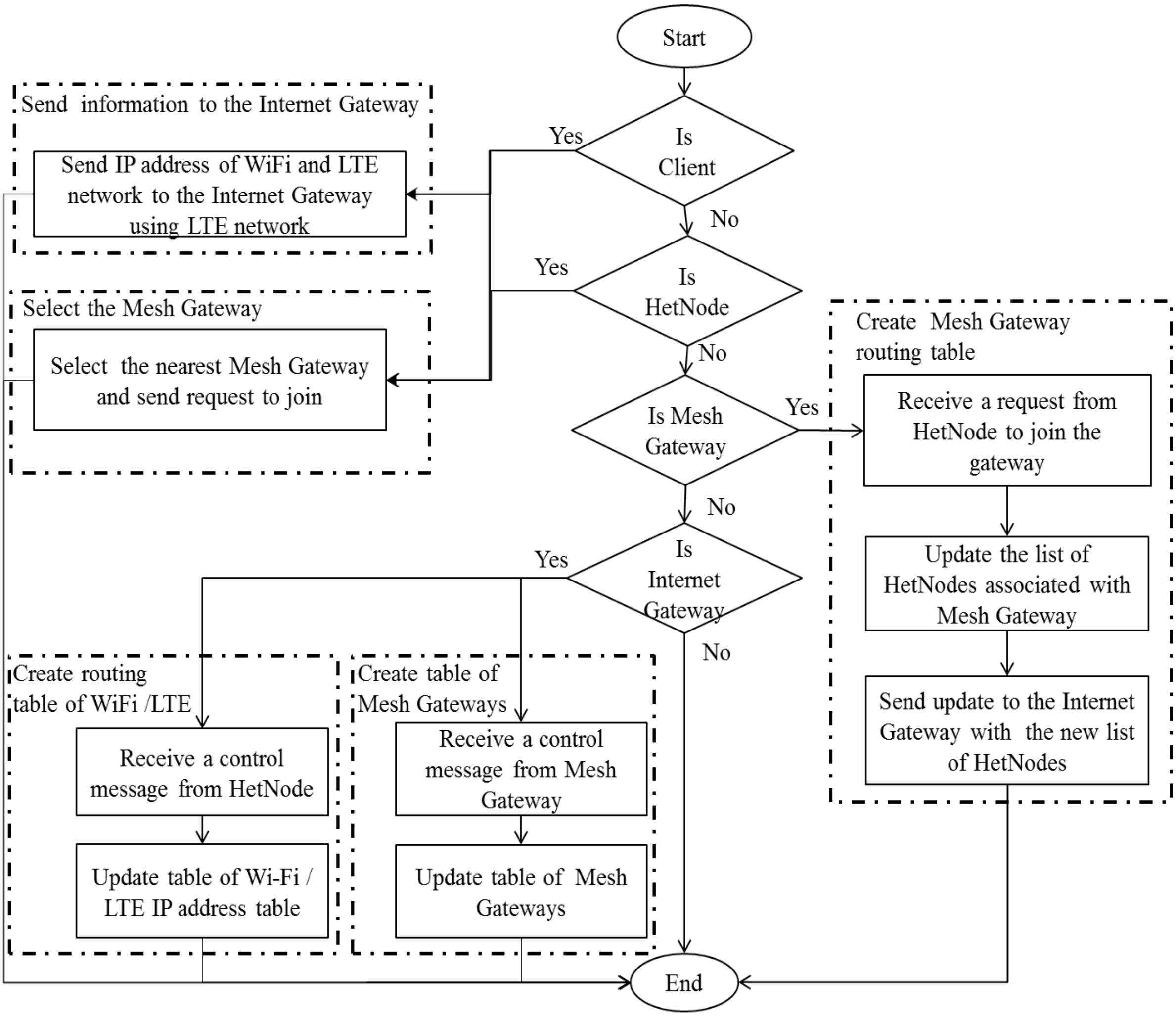

Figure 5-2: Flowchart of creating routing tables.

In the case of Mesh Gateway nodes, the routing table maintains a list of the heterogeneous nodes for which it is responsible in order to connect them to the Internet. Each Mesh Gateway receives request messages from NetNodes and updates the table of NetNodes associated with it. The Mesh Gateways send update messages to the Internet Gateway about their new list of NetNodes. Finally, nodes of type Internet Gateway employ this information to maintain a table to store the available Mesh Gateways and the heterogeneous nodes associated with each Mesh Gateway. The LTE base station forwards all the Internet packets to the Internet Gateway. In client nodes that are equipped with either LTE or Wi-Fi device, no additional routing tables are required. The LTE device communicates directly with the eNB base station while the Wi-Fi device utilises OLSR to select the Mesh gateway based on hop counts and load on the Mesh Gateway.

5.2.2 **Cognitive Heterogeneous Routing Algorithm**

The second part of the proposed routing protocol is the new algorithm developed, referred to here as Cognitive Heterogeneous Routing (CHR), which selects the most suitable transmission technology based on parameters from both of the utilised transmission technologies. CHR employs the generated routing tables to choose the best route to send the traffic demands. The CHR is responsible for selecting the best radio access network while the routing tables maintained by each node find the route to the Internet. In case a NetNode selects Wi-Fi device, it uses the routing table to send the packets to the next hop on the path of the selected Mesh Gateway. CHR adopts the multi-rate medium access control (MAC) protocol for 802.11 that proposed in Chapter 4. This rate adaptation protocol is developed for a WMN environment to consider the collision and interference in the neighbouring nodes. It employs the transmission rate as a metric to measure the quality of the Wi-Fi channel. RARE reduces the transmission rate when interference is identified on the link and increases it when the interference is low. Thus, the algorithm infers that the wireless channel quality is good when the transmission rate is high. This work employs IEEE 802.11a, which supports eight different transmission rates: 6, 9, 12, 18, 24, 36, 48, and 54 Mbps.

A core element of CHR is a new algorithm that is developed to estimate which transmission technology is the best for sending traffic. It is based on reinforcement learning and Q-learning (Watkins and Dayan 1992), in which Q(t_i) is used subsequently to estimate the best action by considering a reward $R(t_i)$ each time an action is taken. The equation of this learning algorithm is calculated as follows::

$$Q(t_i) = (1-\alpha)Q(t_{i-1}) + \alpha[R(t_i) + \gamma Q(t_{i+1}) - Q(t_{i-1})], \tag{5.1}$$

where α is the learning rate ($0 \leq \alpha \leq 1$), t_i is the current time, t_i*-1* is the previous time for i >1, and γ is the discount value. If $\alpha = 0$, then there is no learning in the algorithm; if γ = 0, the reinforcement learning is opportunistic, which maximises only the immediate, short term reward.

CHR, the algorithm proposed in this study, is based on Q-learning to calculate whether the selected transmission technology is improving the network performance by learning from previous actions. It selects an appropriate transmission technology based on parameters from both Wi-Fi and LTE networks. The algorithm has two parts. The first part is the uplink routing algorithm, which is responsible for sending data packets from the heterogeneous nodes to the Internet. The second part is the downlink, which is in charge of transmitting data packets from the Internet to the heterogeneous nodes.

Reinforcement learning is employed in both uplink and downlink transmissions, to estimate the probability of transmitting data packets through each transmission technology. For uplink transmission, each heterogeneous node utilises CHR to select either the LTE or Wi-Fi network. In the downlink communication, the CHR algorithm is utilised by the Internet Gateway node only.

The LTE network employs both the load and the probability of successful transmissions of packets through the network as metrics to measure link quality. The load of the LTE network is estimated by measuring the buffer length of each node. This value is obtained from the radio link control (RLC) protocol layer in the eNB and the heterogeneous node. The RLC is located on top of the MAC layer and is responsible for maintaining the length of transmission buffer and transferring packets from upper layers to the MAC layer using the acknowledgement or un-acknowledgement mode and error correction. Two types of transmission buffers are maintained by the LTE network: one for downlink transmissions and one for uplink transmissions. Thus, the length of the buffer on each node represents its load level. Equation (5.2) (Yang et al. 2013) is utilised to estimate the load on each NetNode.

$$LL^{d}(t_i) = \frac{BufL^{d}(t_i)}{BufL_{\max}}, \tag{5.2}$$

where $LL^d(t_i)$ is the estimated LTE load on heterogeneous node d at time t_i, $BufL^{d}(t_i)$ is the number of packets in the LTE transmission buffer for node d at time slot t_i, and $BufL_{max}$ is the maximum number of packets that the transmission buffer can accept. The higher $LL^d(t_i)$ is ($0 <= LL^d(t_i) <= 1$), the more congested the node is.

In WMN, CHR employs both the transmission rate that each node utilises to transmit its packets during time slot t_i and the probability to access the channel as metrics to calculate the wireless channel quality. Equation (5.3) (Benslimane and Rachedi 2014) is employed to measure the Wi-Fi channel quality.

$$CQW^{d}(t_i) = \frac{RW^{d}(t_i)}{RW_{\max}}, \tag{5.3}$$

where $CQW^d(t_i)$ is the Wi-Fi channel quality for node d at time t_i and $RW^d(t_i)$ is the transmission rate for the Wi-Fi device at node d at time t_i. According to *RARE*, the rate adaptation algorithm proposed in the previous Chapter and employed by CHR, the node increases the transmission rate if the estimated interference in the neighbouring nodes is low. Thus, a higher transmission rate means lower interference on the node and higher probability of sending the packets successfully. RW_{max} is the maximum transmission rate that the WiFi transmission technology can support.

In order to route the packets from the heterogeneous nodes to the Internet and vice versa, the CHR algorithm is utilised for both uplink and downlink transmission. A new algorithm based on reinforcement learning is utilised to estimate the probability of transmitting data packets through each transmission technology. Figure 5.3 shows the flowchart of the CHR algorithm.

The flowchart shows the steps of employing *CHR* algorithm to utilise information maintained by each routing table generated using the proposed routing protocol. The flowchart is divided into two parts. The first part is exploration, in which the algorithm initialises the parameters employed in the algorithm. Then, the learning stage starts by evaluating each action performed by the network nodes.

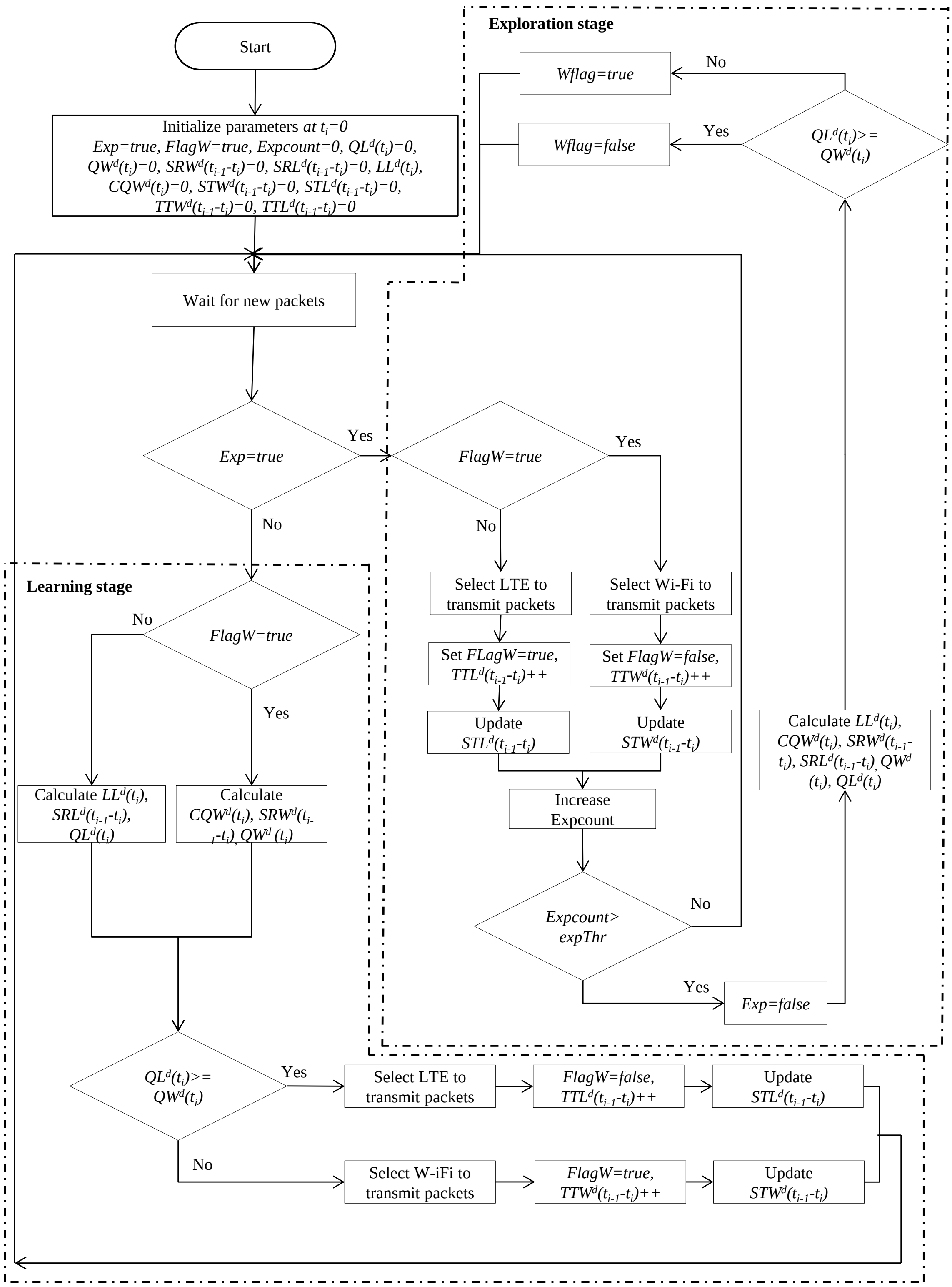

Figure 5-3: Flowchart of CHR routing algorithm.

In particular, the algorithm begins by setting the network parameters to their defaults values, as shown in the flowchart. The exploration stage involves sending a specific number of packets using the Wi-Fi network and the LTE network. A flag variable (*FlagW*) is used to indicate whether the Wi-Fi or the LTE device is being used during the exploration stage. Then a counter variable (*Expcount*) is employed to control the number of exploration required to be done in this stage. The length of the exploration does not have a great impact on the system throughput, as the algorithm will converge during the reinforcement learning cycles. After finishing the exploration stage, the algorithm starts the learning stage in which each node calculates the probability of transmitting data successfully for each transmission technology by learning from previous actions using Q-learning.

Equation (5.4) shows how Q-learning equation (5.1) (WATKINS and Dayan 1992) is adapted for WMN and incorporated in the CHR algorithm to calculate the probability of transmitting data successfully.

$$QW^d(t_i) = (1-\alpha)QW^d(t_{i-1}) + \alpha[SRW^d(t_{i-1}-t_i) + CQW^d(t_i) - QW^d(t_{i-1})], \quad (5.4)$$

where $QW^d(t_i)$ represents the probability of accessing the Wi-Fi channel for node *d* at time t_i, α is the learning rate (α=0 there is no learning in the algorithm), $SRW^d(t_{i-1}-t_i)$ is the success rate of node *d* since the last update of the transmission rate, calculated using equation (5.5) (Benslimane and Rachedi 2014). $CQW^d(t_i)$ is the Wi-Fi channel quality for node *d* at time t_i and is calculated using equation (5.3).

$$SRW^d(t_{i-1}-t_i) = \frac{STW^d(t_{i-1}-t_i)}{TTW^d(t_{i-1}-t_i)}, \quad (5.5)$$

where $STW^d(t_{i-1}\text{-}t_i)$ is the number of successful transmissions from t_{i-1} until t_i a value which is obtained from the MAC layer of the IEEE 802.11 device on heterogeneous node *d* by counting the number of received acknowledgements for each transmission; and $TTW^d(t_{i-1}\text{-}t_i)$ is the total number of transmissions for node *d* using Wi-Fi from t_{i-1} to t_i.

Q-learning equation (5.1) (WATKINS and Dayan 1992) is adopted by the *CHR* algorithm equation (5.6) to estimate the probability of transmitting data successfully using the LTE network.

$$QL^d(t_i) = (1-\alpha)QL^d(t_{i-1}) + \alpha[(SRL^d(t_{i-1}-t_i) + (1-LL^d(t_i))) - QL^d(t_{i-1})], \quad (5.6)$$

where $QL^d(t_i)$ represents the probability of accessing the LTE channel for node *d* at time t_i, α is the learning rate, $SRL^d(t_{i-1}\text{-}t_i)$ is the success rate in LTE device of node *d* since the last update of the probability to access LTE network, which is calculated using equation (5.7), and $LL^d(t_i)$ is the estimated load in LTE device on node *d* at time t_i and is calculated using equation (5.2).

$$SRL^d(t_{i-1}-t_i) = \frac{STL^d(t_{i-1}-t_i)}{TTL^d(t_{i-1}-t_i)}, \quad (5.7)$$

where $STL^d(t_{i-1}\text{- }t_i)$ is the number of successful transmissions for node *d* during a period (t_{i-1}, t_i) using LTE network and this information is obtained from RLC layer using acknowledgement mode, $TTL^d(t_{i-1}\text{- }t_i)$ is the number of transmissions using LTE during a period (t_{i-1}, t_i). After finishing the exploration stage, each node waits for new packets ready for transmission and then updates the probability to select the transmission technology ($QL^d(t_i)$ or $QW^d(t_i)$). Thereafter, the algorithm selects the transmission technology with the higher probability to send the packets successfully (i.e. higher Q-value). Then, CHR updates all the parameters and waits for the next packets.

5.3 Performance Evaluation

In this section, the heterogeneous wireless mesh network is evaluated using the ns-3 simulator (ns-3 n.d.), which is a widely used tool for evaluating and validating wireless networks. In particular, this work uses the LENA NS-3 LTE Module model. The proposed network is compared in terms of throughput with LTE-only networks, Wi-Fi-only networks, and a random network (R) that randomly allocates LTE or Wi-Fi network for each node.

5.3.1 Simulation Setup

Table 5.1 shows the network parameters used in the simulation. Two types of scenarios are employed in order to evaluate and validate the proposed network. The first scenario consists of grid topologies in which NetNodes are distributed in a grid with 100 meters between each node. The second scenario consists of random topologies in which all nodes are distributed randomly in 1000 by 1000 meters area. In both scenarios, there are five Mesh Gateways distributed in the network and the LTE eNB is allocated in the centre. In order to analyse the performance of the proposed network, different loads are applied to the network using 19 and 30 nodes transmitting simultaneously for both uplink and downlink transmissions.

5.3.2 Evaluating and Validating Results

The performance of HetMeshNet is compared with LTE-only and random networks, using different numbers of radio resource blocks (RB), and Wi-Fi-only networks.

Two types of scenarios are employed to evaluate the proposed system: one to test the uplink and one to test the downlink. In the uplink scenarios, the nodes (except the Mesh

Table 5-1: Simulation setup.

Simulation Parameters	**Assigned Value**
Topology	Grid and random
Number of Mesh Gateways	5
Number of LTE eNB	1
Number of heterogeneous nodes	30
IEEE 802.11 MAC	802.11a
Number of flows	19 and 30
Packet size	1500 bytes
Packet generation rate	0.1 second
Topology-covered area	1000 *1000
Transmission rates for Wi-Fi networks	6, 9, 12, 18, 24, 36, 48, 54Mbps
Mobility	Static (none)

Gateway nodes) generate user datagram protocol (UDP) traffic with the same rate and the sole destination is the Internet. This simulates the uplink traffic from customer terminals to the Internet. Grid and random topologies are employed in the simulation and two different loads are applied to the network using 19 and 30 nodes transmitting simultaneously to the Internet. A second scenario is utilised to show how the algorithm adapts to the change of the load amount during the simulation.

The simulation results for the uplink scenarios indicate a significant improvement in system throughput for the proposed heterogeneous system compared with the benchmark networks. Figure 5.4 – 5.8 show the throughput results for the adopted uplink scenarios compared with LTE-only network, Wi-Fi-only network, and random networks.

Each figure shows the average throughput for each network; the results are represented by a box and whisker graph, where the lower box represents the average throughput quartile lower than the median and the upper box represents the average throughputs higher than the median. The upper and lower whiskers represent the highest and lowest value of the results, respectively. In LTE-only and random networks, two different bandwidths are employed in the evaluation of the proposed network model. The bandwidth in LTE network is represented by the total number of RBs available for the user equipment in the network. In the evaluation, 25 and 50 RBs are utilised by LTE network and the HetMeshNet in the simulation.

The same scenarios are employed to evaluate the downlink communication in the HetMeshNet. In downlink scenarios, UDP traffic is generated from the Internet and the destination is the heterogeneous nodes in the networks. The purpose of simulating downlink traffic is to show how the proposed algorithm acts when the data are coming from the Internet. In downlink, if Wi-Fi is selected, the intermediate nodes cannot switch back to LTE while in the uplink transmission intermediate nodes could switch from Wi-Fi to LTE. The simulation results show a significant improvement in system throughput. Figure 5.9 – 5.13 show the throughput results for the downlink algorithm while Figure 5.8 and 5.13 apply different amounts of load on the network for uplink and downlink transmission respectively to show how the network adapts to different traffic demand during the simulation. Moreover, another set of scenarios is employed to evaluate the system performance with a different value of α (learning rate in reinforcement learning). If α is zero, it means the system utilises only the current state of the network with no learning in the system. The simulation results indicate that the network with no learning shows the worst performance in terms of throughput compared with other values of α (learning is presented). Figure 5.14 and 5.15 show the throughput results of CHR using different values of α to demonstrate how the network works without learning, from the results, α with a value higher than 0 (learning is presented in the algorithm) indicates better throughput results compared to the network with no learning (α=0). These results indicate that considering previous network parameters in selecting the radio access technology improve the network performance. Figure 5.16 shows the behaviour of the network throughput at different times with different numbers of transmission nodes. In this scenario, it shows how the proposed algorithm reacts to the change of load on the network. The results indicate that the proposed algorithm outperforms the benchmark networks; for example, when the number of transmitting nodes is 15, the average throughput of the CHR is about 1.7 Mbps with a bandwidth of 25 RB, while the LTE only network with a bandwidth of 50 RB is 1 Mbps (increase with 70%) and with a bandwidth of 25 RB is 0.5 Mbps (an increase of 240%). Figure 5.17 shows the behaviour of the network with a constant number of client nodes, which are allocated to different NetNodes with a mobility of client nodes in order to demonstrate how the learning algorithm react to a change in the bandwidth request. This scenario employs random walk mobility model to simulate the movements of client nodes in 1000 * 1000 meters area. The results indicate the learning algorithm adapts very well with the change in the load demands in the network compared with the benchmark networks in term of network throughput. For example, the average network throughput of CHR with a bandwidth of 25 RB is around 2 Mbps while LTE and random networks with as twice bandwidth as CHR achieve around 1 and 1.5 Mbps, respectively.

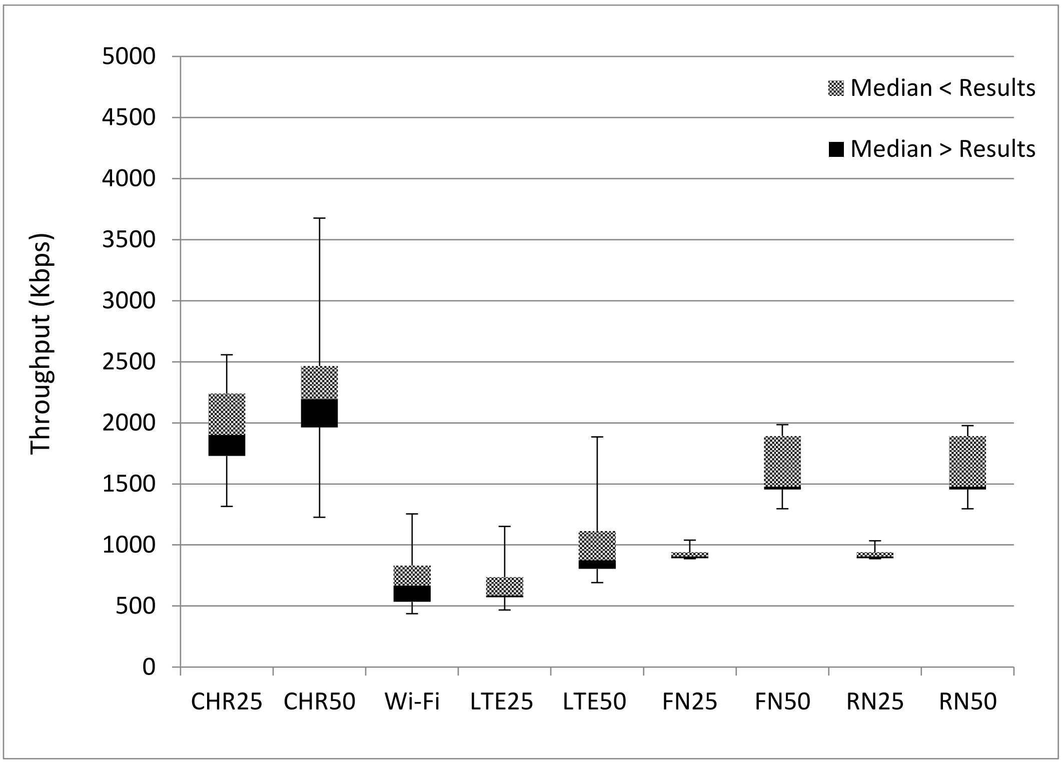

Figure 5-4: Uplink grid scenario with 19 nodes.

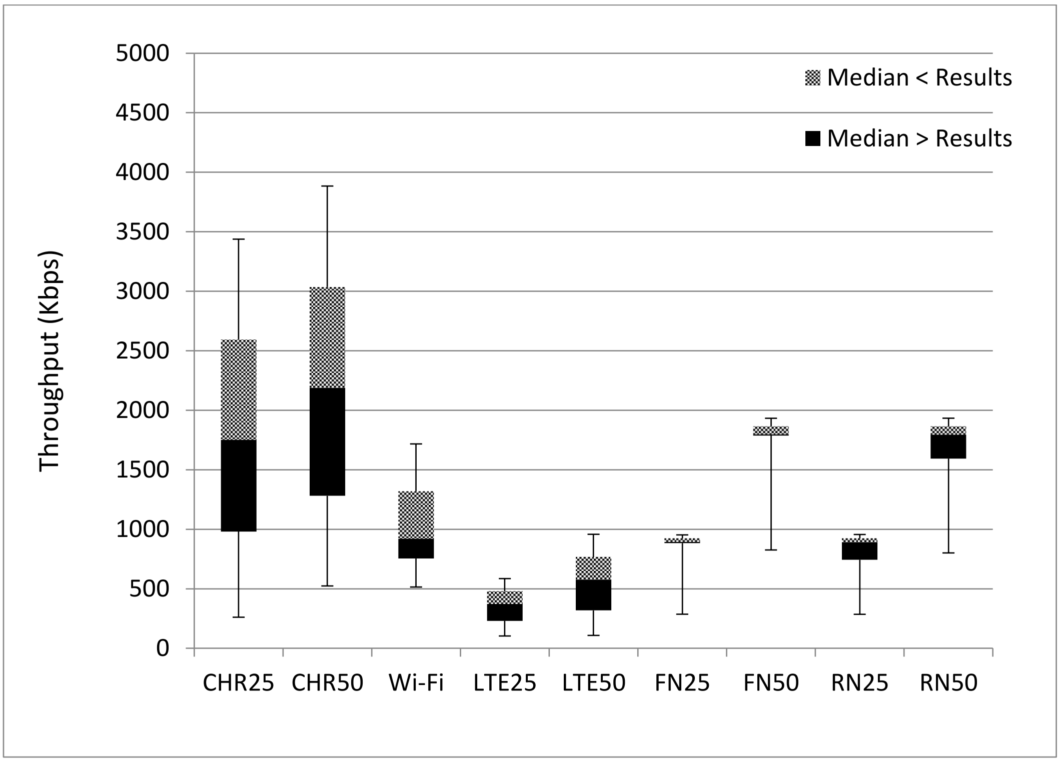

Figure 5-5: Uplink random scenario with 19 nodes.

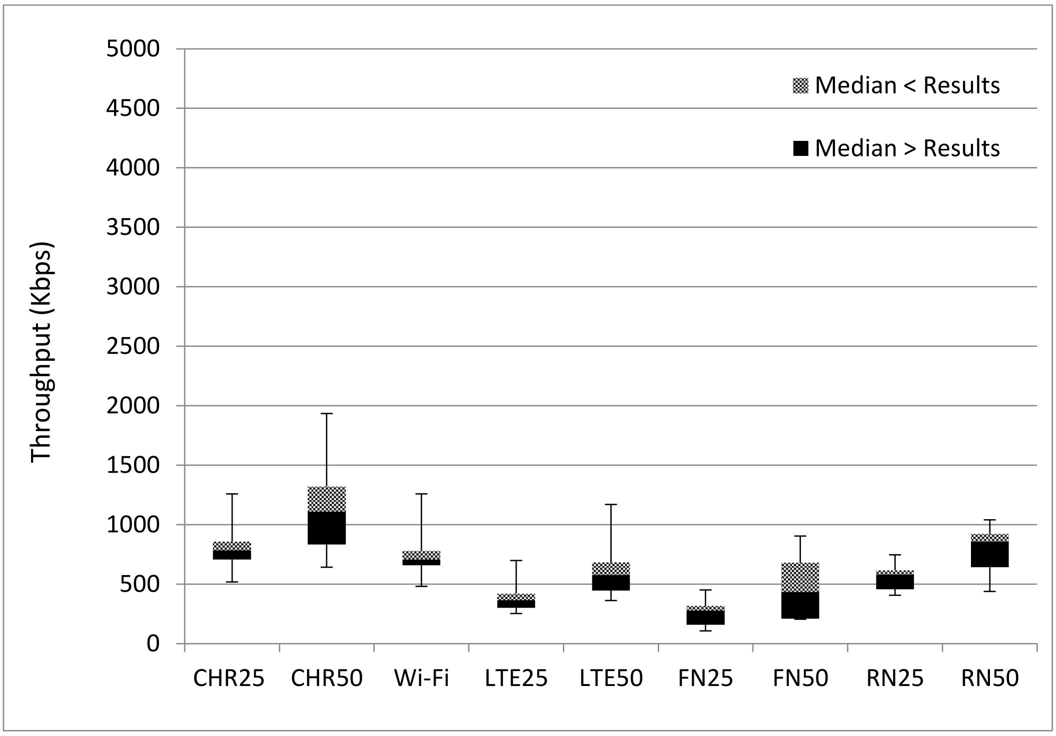

Figure 5-6: Uplink grid scenario with 30 nodes.

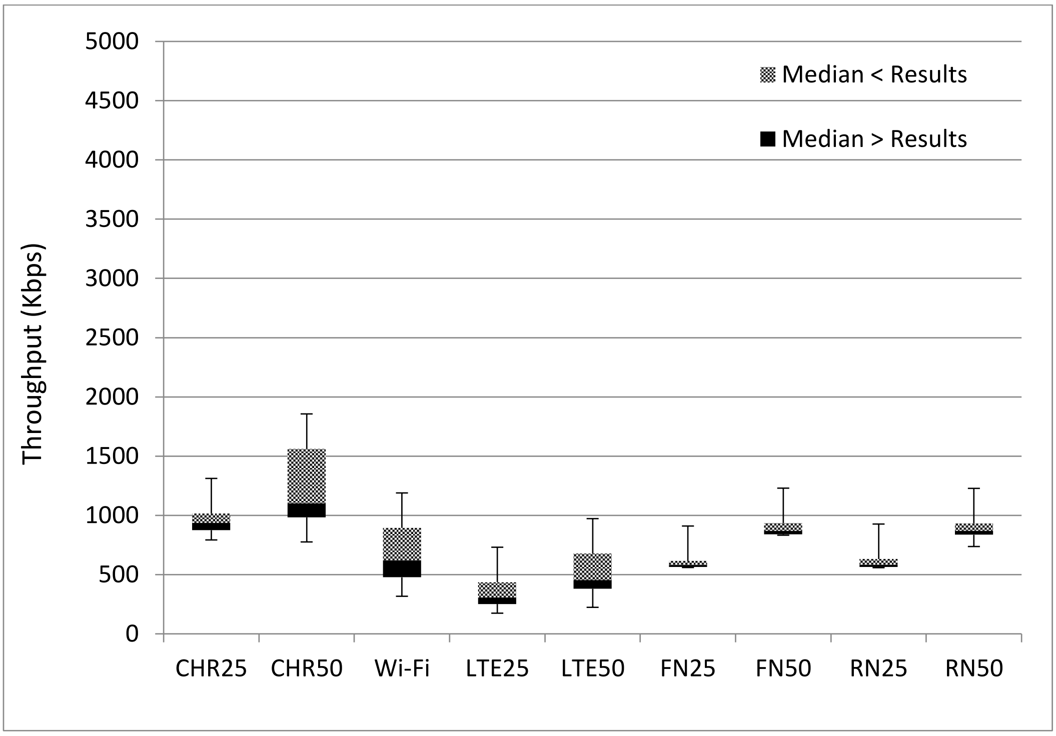

Figure 5-7: Uplink random scenario with 30 nodes.

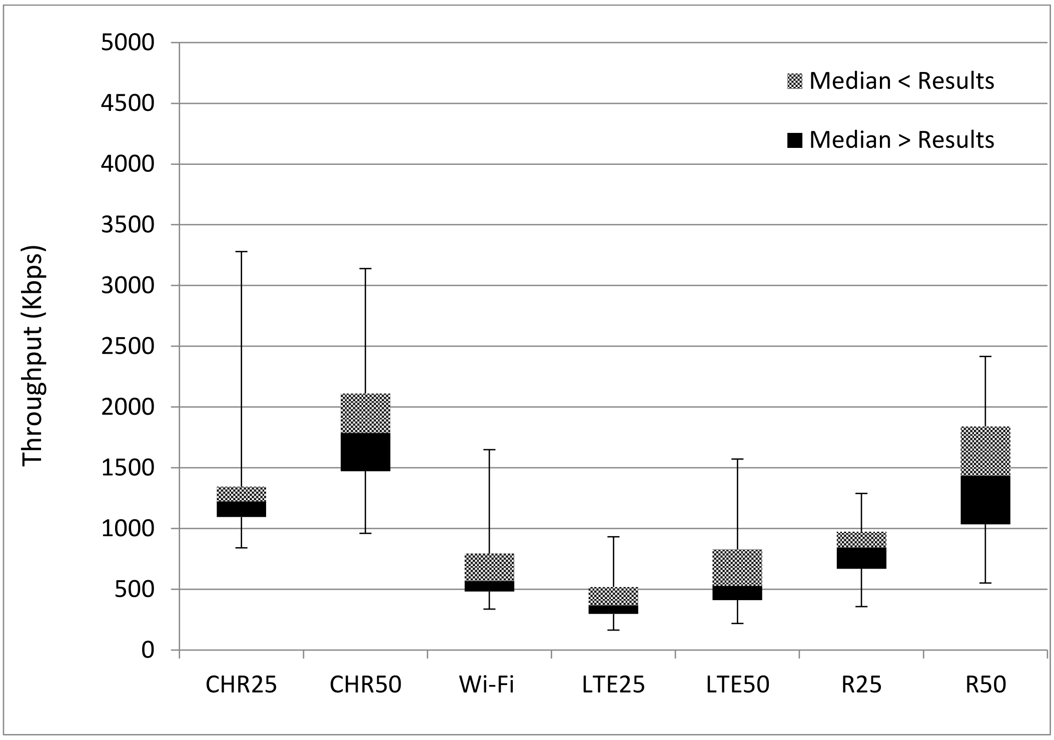

Figure 5-8: Different amount of load during the simulation on uplink.

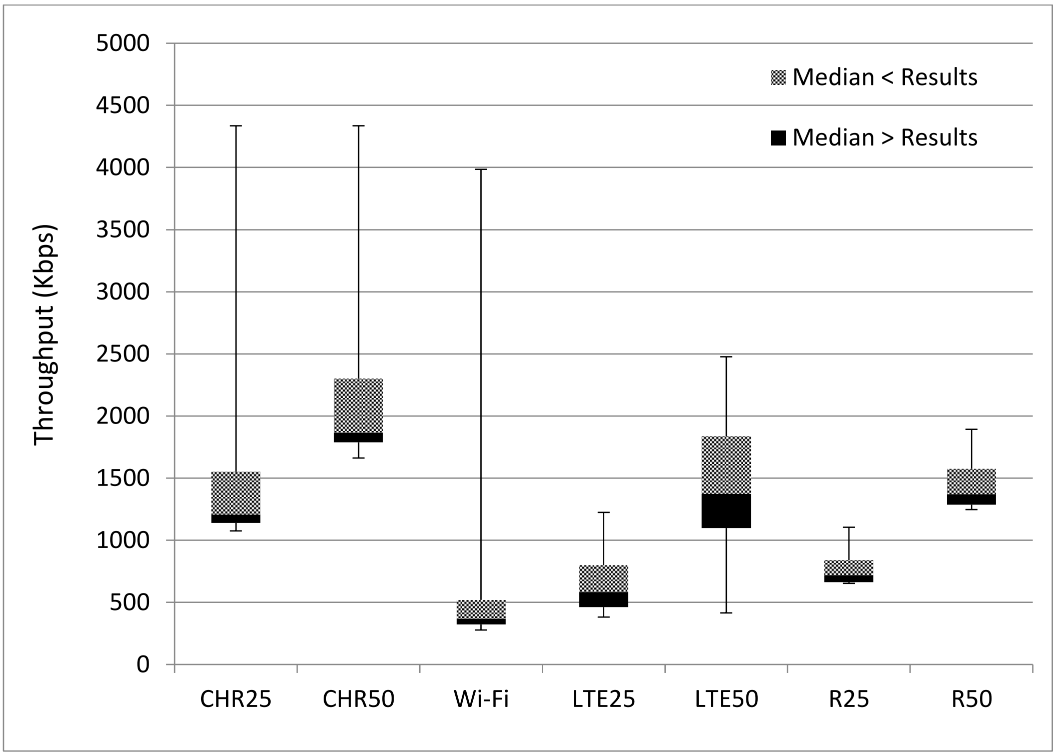

Figure 5-9: Downlink grid scenario with 19 nodes.

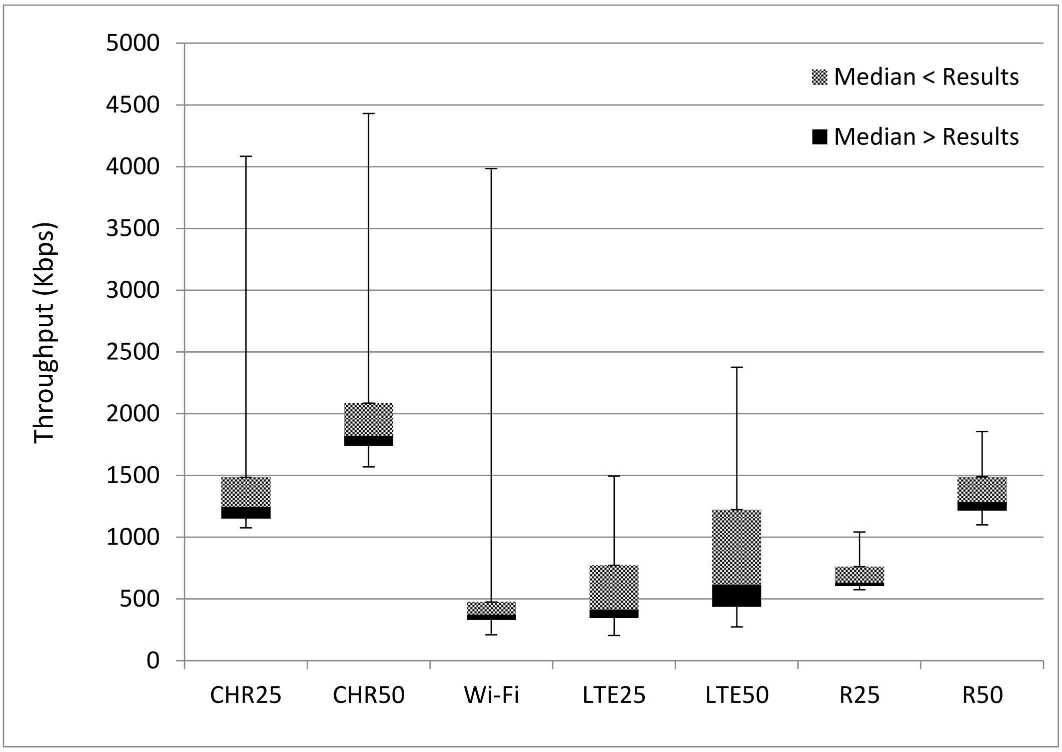

Figure 5-10: Downlink random scenario with 19 nodes.

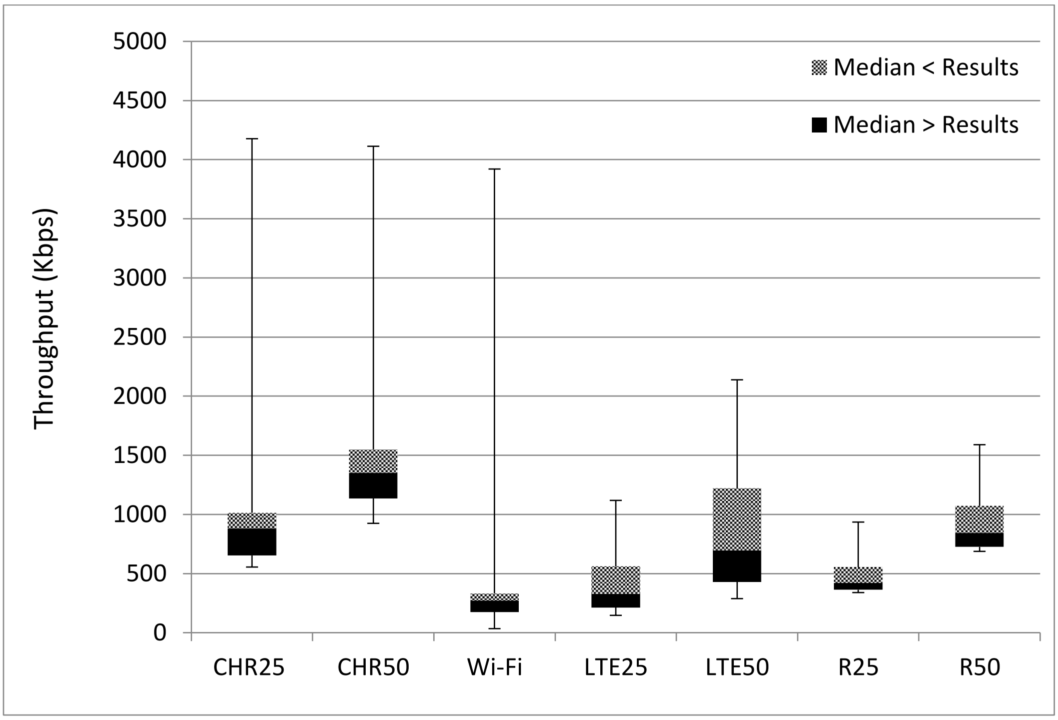

Figure 5-11: Downlink grid scenario with 30 nodes.

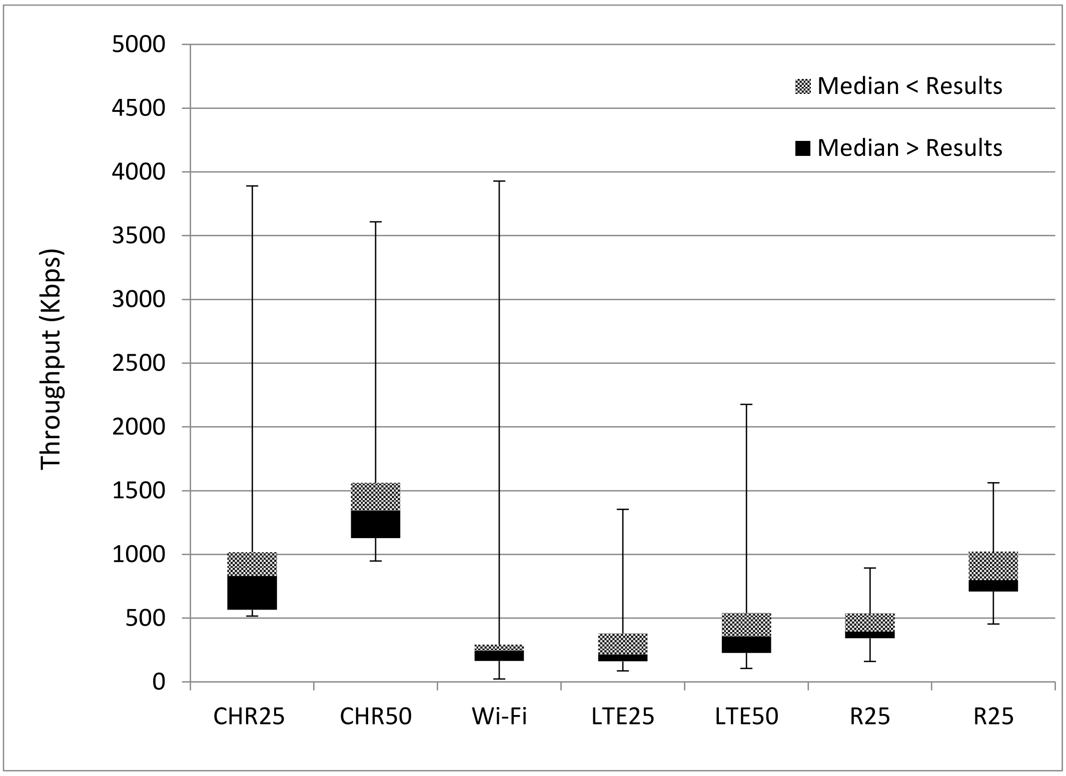

Figure 5-12: Downlink random scenario with 30 nodes.

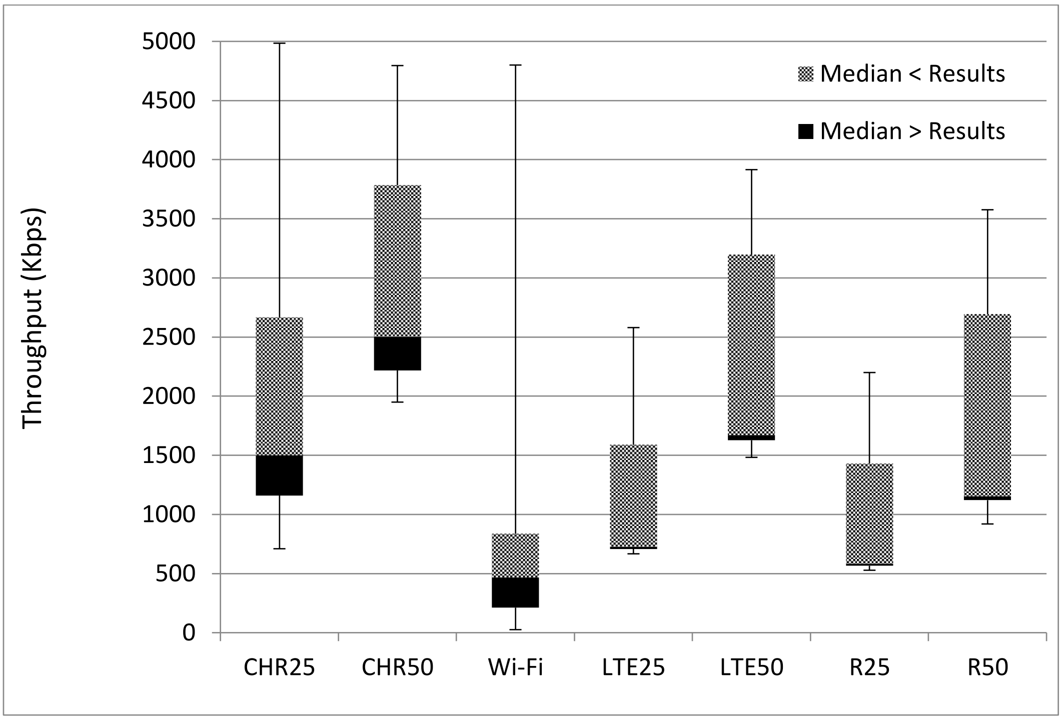

Figure 5-13: Different amount of load during the simulation on downlink.

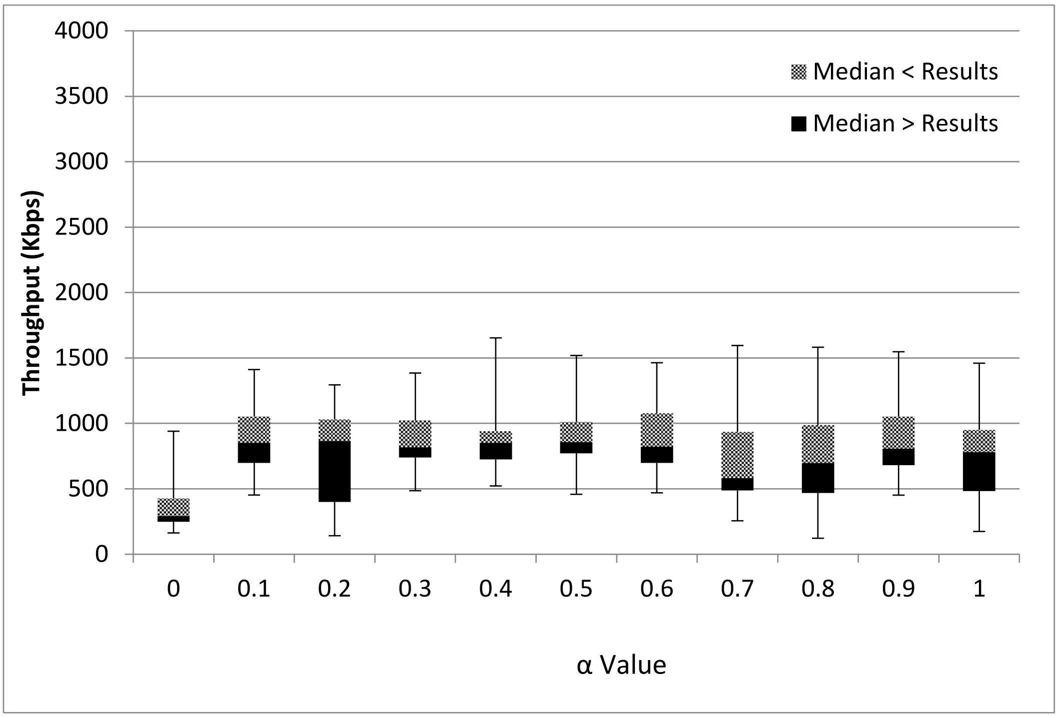

Figure 5-14: HetMeshNet performance with different value of α in grid scenario (0 ≤ α ≤ 1).

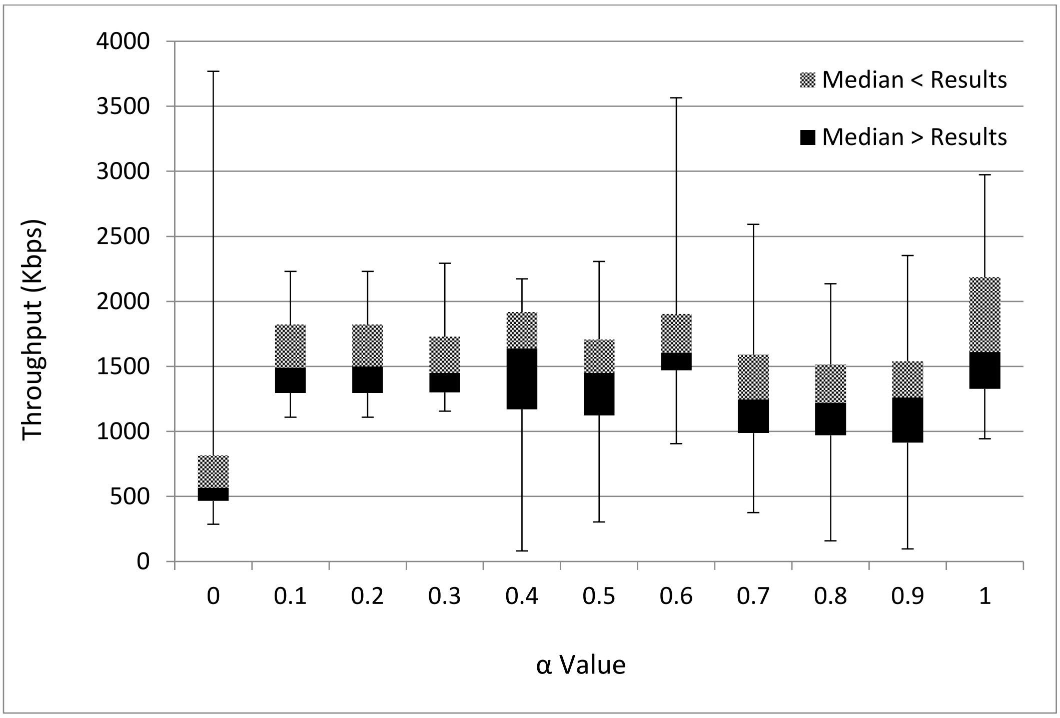

Figure 5-15: HetMeshNet performance with different value of α using different amount of load during the simulation (0 ≤ α ≤1).

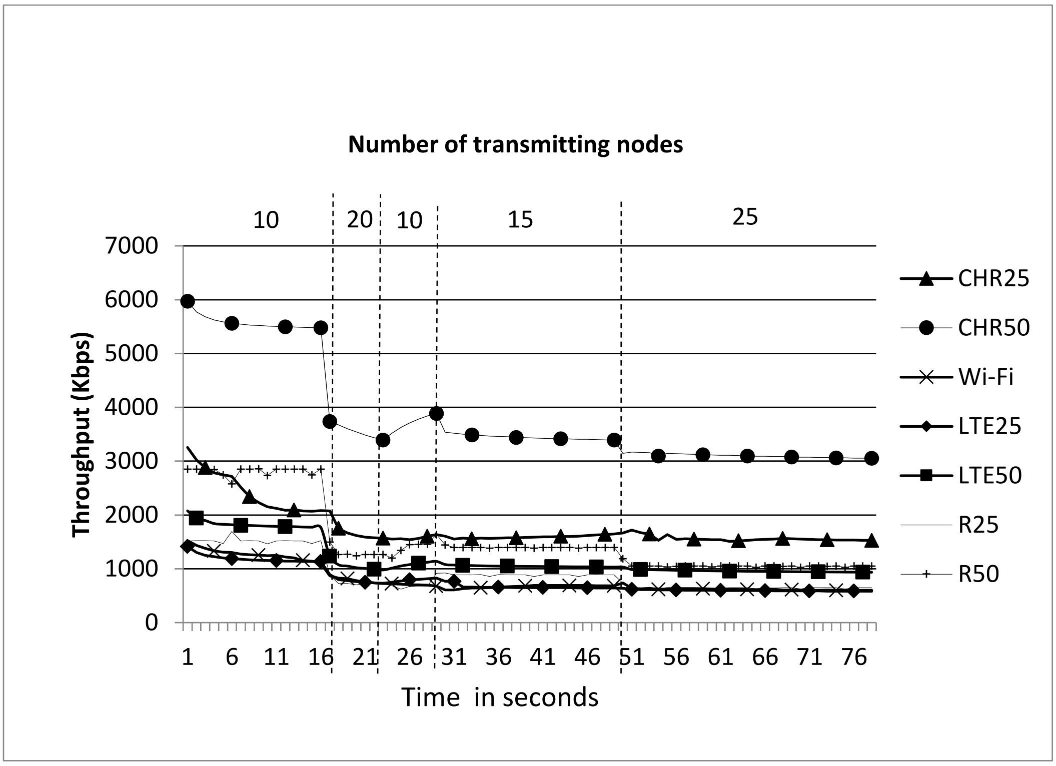

Figure 5-16: Average network throughput over time with different number of transmission nodes.

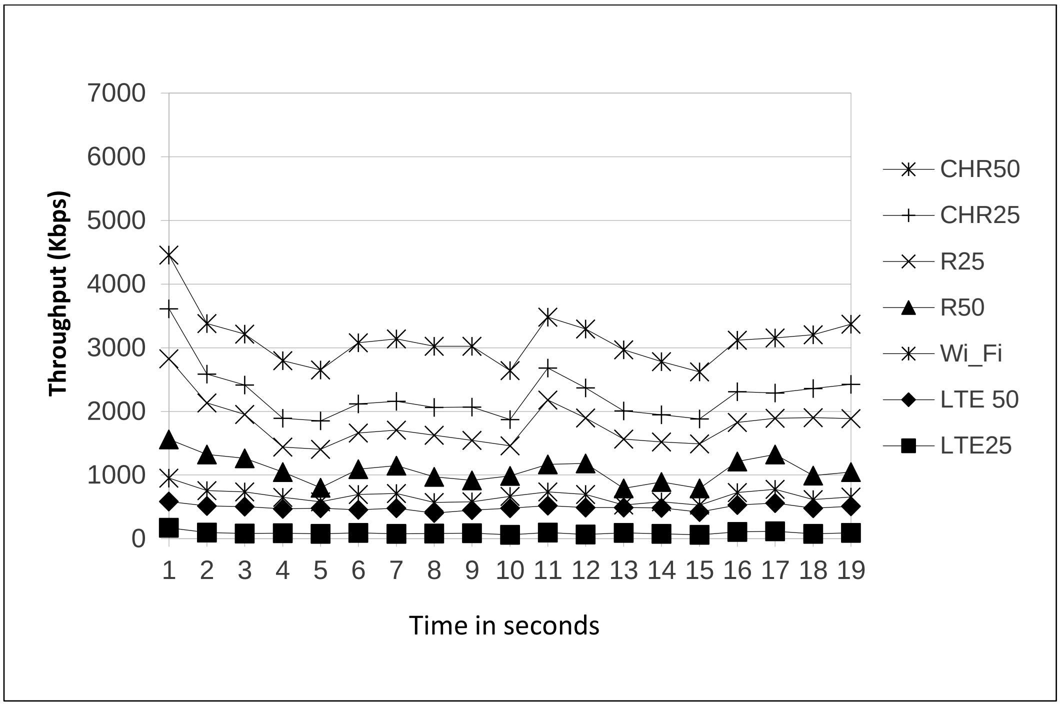

Figure 5-17: Average network throughput with constant number of nodes and mobility.

ANOVA statistical test was performed on the results from each scenario to verify that there is a systematic enhancement in the network that causes the throughput improvement. Equation (5.8) (Scheffe 1959) is employed to confirm that the algorithms are statistically different.

$$F > F_{Crit,} \qquad \text{5-8}$$

where F is the ANOVA test statistics and F_{Crit} is the critical value extracted from the F-distribution table. Another parameter from the ANOVA test is p, which is the probability of having differences that happen purely by chance, and the preferred value is smaller than 0.05. Thereafter, in order to verify that the HetMeshNet has produced higher throughput than the benchmark algorithms, the results from each scenario are submitted to the Fisher's LSD test. In each scenario, there are 19 or 30 throughput results for each type of network. The average throughput value of these results is calculated for each network ($LTE25_{avr}$, $LTE50_{avr}$, $Wi\text{-}Fi_{avr}$, $CHR25_{avr}$, and $CHR50_{avr}$). Next, if $|CHR25_{avr} - LTE25_{avr}| > LSD$, then the two averages are statistically different. Table 5.2 and 5.3 show the ANOVA and LSD results for each scenario, respectively.

The results show that the average throughput of the HetMeshNet outperforms the LTE network even when the LTE network utilises twice as much bandwidth as CHR, while the Wi-Fi networks may suffer from high loss due to interference and collision. In Figure 5.4, the CHR algorithm with LTE bandwidth of 25 RB achieves average uplink throughput between 1.6 and 2.3 Mbps for 50 % of the results, while the LTE network with 50 RB achieves between 0.7 and 1.2 Mbps, which shows how the CHR outperforms LTE only network with about 183% by employing less bandwidth (half of the bandwidth) and in Figure 5.8 the CHR25 increases the network throughput with about 200%.

In the downlink transmission, the throughput improvement in some scenarios is lower than that in the uplink due to the fact that in downlink the LTE network employs multiple input and multiple output (MIMO) antenna which increases the total throughput of a connection in the LTE networks. For instance, Figure 5.9 shows the average throughput of the CHR with 50 RB with about 1.7 Mbps while the LTE network with 50 RB achieves around 1.3 Mbps (the improvement is about 26%). This method improves the network performance and also reduces the cost of buying more licensed frequencies (LTE frequency) by utilising unlicensed Wi-Fi frequencies instead. The results obtained from the HetMeshNet mitigate the poor performance of the Wi-Fi network through the use of the LTE network, as Wi-Fi-only networks suffer from interference. Finally, Figure 5.17 shows the number of transmission packets on each transmission device and also the number of packets that initially started with Wi-Fi and then switched back to the LTE network after one or more hops for example, in node 4 about 45% of the packets are switched from Wi-Fi network to LTE network. This figure shows how the networks dynamically switch between the transmission technologies.

Table 5-2: Analysis Of Variance test results.

Network Scenario	***F***	F_{crit}	***P***
Uplink 19 Nodes Grid	50.5	2.3	$p < 0.001$
Uplink 19 Nodes Random	21.5	2.3	$p < 0.001$
Uplink 30 Nodes Grid	33.2	2.9	$p < 0.001$
Uplink 30 Nodes Random	28.8	2.9	$p < 0.001$
Uplink Different Number of Nodes Transmitting during the Simulation	60.2	2.4	$p < 0.001$
Downlink 19 Nodes Grid	15.4	2.4	$p < 0.001$
Downlink 19 Nodes Random	15.2	2.4	$p < 0.001$
Downlink 30 Nodes Grid	14.3	2.4	$p < 0.001$

Downlink 30 Nodes Random	17.8	2.4	$p < 0.001$
Downlink Different Number of Nodes Transmitting during the Simulation	6.0	2.4	$p < 0.001$

Table 5-3: LSD test results.

Network Scenario	**Throughput Average for the Networks (Kbps)**					**LSD**
	LTE25	***LTE50***	***Wi-Fi***	***CHR25***	***CHR50***	
Uplink 19 Nodes Grid	663.5	1027.2	703.9	1967.9	2315.4	268.9
Uplink 19 Nodes Random	366.2	570.2	1057.5	1734.0	2134.2	413.6
Uplink 30 Nodes Grid	379.6	600.9	739.9	796.3	1111.5	117.8
Uplink 30 Nodes Random	355.6	562.3	679.5	1022.3	1331.5	177.4
Uplink Different Number of Nodes Transmitting during the Simulation	420.8	668.6	673.2	1357.2	1839.7	208.4
Downlink 19 Nodes Grid	658.2	1468.2	732.9	1597.2	2273.2	470.3
Downlink 19 Nodes Random	558.1	846.9	725.3	1644.3	2233.5	502.9
Downlink 30 Nodes Grid	418.6	873.9	485.0	1113.5	1577.3	347.5
Downlink 30 Nodes Random	346.5	524.2	471.5	1078.6	1557.9	333.2
Downlink Different Number of Nodes Transmitting during the Simulation	1120.5	2334.5	1566.4	2357.1	2965.5	516.4

The HetMeshNet improves the overall network throughput compared to the LTE network that utilises twice as much bandwidth. Furthermore, Figure 5.18 shows that many of the nodes utilise Wi-Fi bandwidth, which is cheaper than LTE because Wi-Fi frequencies are unlicensed. The simulation experiments show that the proposed model enhances nodes throughput by up to 200% on the uplink and downlink compared with the LTE and Wi-Fi networks and also overcomes the problem of throughput degradation in WMNs under high traffic density.

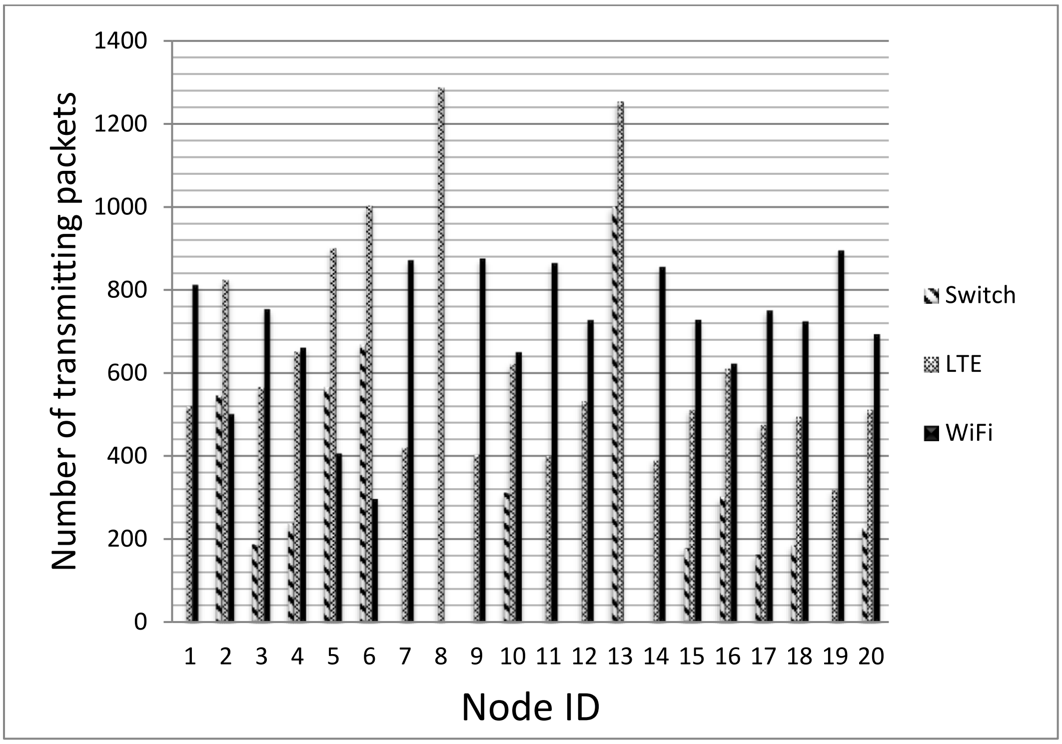

Figure 5-18: Number of transmitting packets for each wireless technology.

5.4 Summary

This chapter introduces a new heterogeneous network architecture in which LTE and Wi-Fi wireless devices are utilised in order to benefit from the bandwidth of each transmission technology. In addition, a new routing protocol for heterogeneous wireless mesh networks is developed, which selects dynamically the transmission technology in order to increase the overall network capacity and enhance the average throughput. Moreover, a new routing algorithm is proposed for the needs of the routing protocol, which estimates the cost of transmitting the traffic through each network. The proposed algorithm considers the traffic load on the LTE network as a metric in order to estimate the cost of transmission over LTE, and it uses the transmission rate as a metric for the Wi-Fi mesh network. The simulation results showed that the proposed network achieved up to 200% more throughput compared with Wi-Fi-only networks and LTE-only networks.

The heterogeneous network architecture managed the different wireless devices as a part of a single virtual network. The LTE network can be utilised to avoid congested Wi-Fi nodes and high interference paths in the WMN. The WMN offloads the load of the LTE network, reduces the cost of using additional licensed frequency bands and forwards the data to another node when the LTE throughput is degrading.

Chapter 6

Semantic Reasoning System for Heterogeneous WMNs

This chapter advocates the use of semantic reasoning based on ontologies in cognitive networks to abstract the network infrastructure from the control system and improve the performance of heterogeneous wireless mesh networks (WMN). The proposed semantic reasoning establishes an extendable smart middleware that automatically manages, configures and optimises the performance of various networks

The novelty of the proposed middleware is that it uses semantic reasoning with parameters from LTE and WMN architectures to enable each node in the heterogeneous network to self-configure and be aware of the surrounding environment and any additionally installed transmission devices. Semantic reasoning simplifies the process of managing different radio access networks by using ontologies to capture network parameters and representing the fundamental relationships among the different wireless devices, which can be understood by machines.

This chapter is organised in four sections. Section 6.1 introduces the network layout utilised in this chapter. Section 6.2 describes the proposed semantic system, which is then experimentally evaluated in section 6.3. Finally, section 6.4 summarises the chapter.

6.1 Network Layout

This Chapter extends the heterogeneous mesh network model proposed in the previous Chapter by three different architectures, WMN, VANET, and LTE, to use the different frequency bands of each network. WMNs and VANETs utilise IEEE 802.11n and IEEE 802.11p, respectively. For this study, two scenarios were proposed to evaluate the semantic reasoning system on heterogeneous wireless networks. The first scenario was the urban heterogeneous network scenario in which different amounts of traffic demands were applied to the system. The second scenario was the VANET heterogeneous network scenario, which used several network architectures to demonstrate how the proposed semantic reasoning system could be extended to control other network types. In the first scenario, the client nodes consider the coexistence of WMN and LTE networks and transmit data to the Internet using one of the available radio access networks (RAN) (IEEE 802.11n or LTE) in the heterogeneous network while the second scenario introduces the use of VANET network in which a roadside base stations uses three RANs (LTE, 802.11n and 802.11p). Figure 6.1 shows an example of how the heterogeneous networks architecture presented in Chapter 5 is extended using VANET network.

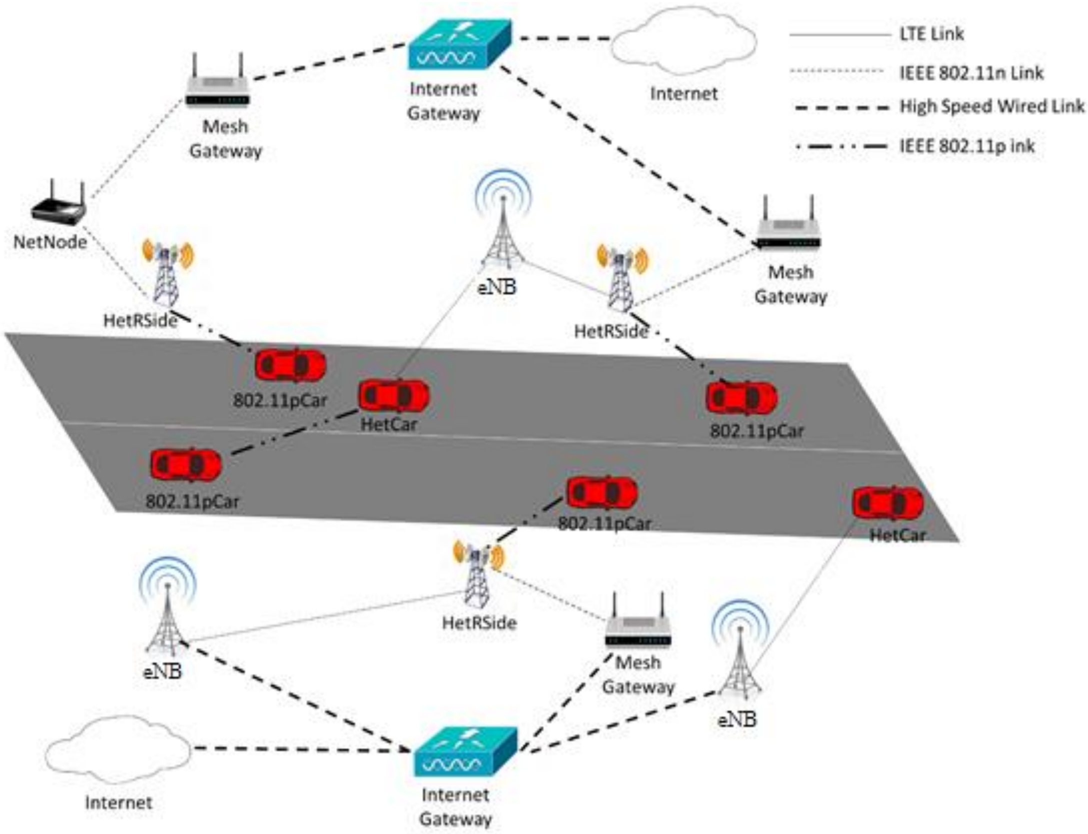

Figure 6-1: VANET heterogeneous network scenario.

The heterogeneous network in this Chapter utilises multiple LTE network cells to show how the network function with more than one LTE cell.

The heterogeneous network model extends the network architecture in Chapter 5 with the following node types:

- 802.11pCars: Cars that are part of the VANET network and employ only IEEE 80211p
- HetCars: Cars that are part of the VANET network and are equipped with both IEEE 802.11p and LTE radio access networks.

- HetRSide: Roadside units that employ IEEE 802.11p, 802.11n, and LTE radio access networks. These nodes connect the cars on the road to the WMN and LTE networks.

In this network model, the ClientNodes connect to the Internet through IEEE 802.11n or the LTE network. The HetCars connect to the Internet either through IEEE 802.11p or the LTE radio access network. 802.11pCars connect to the Internet through IEEE 802.11p RAN. The NetNodes are responsible for forwarding client data to and from the Internet using either LTE or IEEE 802.11n based on QoS parameters. The HetRSides communicate with 802.11pCars and HetCars through the IEEE 802.11p, then forward the data using either LTE or IEEE 802.11n to the Internet.

The proposed reasoning system allows ClientNodes to forward the data from other clients to the Internet and gain some credit in return. Enabling ClientNodes to participate in the network infrastructure will reduce the load on the network backbone and will also allow users to gain credits by forwarding data.

The selection of transmission technology to forward the data is determined based on QoS parameters described in the next section.

6.2 Semantic System for Heterogeneous Network

This section provides a detailed description of the semantic system, which is part of the proposed cognitive network model. It consists of a semantic knowledge base and a semantic inference engine. An ontology of heterogeneous networks and a rule base are developed as part of the semantic knowledge base, while the semantic inference engine contains the instances of the ontology in the knowledge base and the fuzzy-based reasoner.

Ontologies are used to define the binding properties, types, and relationships which is used to build the heterogeneous network knowledge base. Cross-layer properties from each device are used to create relationships between the different networks architectures using various RAN.

6.2.1 Heterogeneous Network Ontology

The QoS parameters of each network in the heterogeneous network are stored using ontology classes, properties, and relationships. Standard ontology languages define a set of classes, subclasses, properties, and relationships, such as OWL (W3C OWL Working Group 2012), and resource description framework (RDF) or RDF schema (Hayes and Mcbride 2004).

This study used extensible markup language (XML) as a platform to create ontology classes of heterogeneous wireless networks. XML is platform independent, which enables the proposed semantic reasoning system to be used with any smartphone, personal computer, or computer-based object. Moreover, the ontology suggested in this work is relatively simple and does not need all the expressiveness that is provided by other standard ontology languages. Using an XML-based approach resulted in a simple, lightweight knowledge base system that could work on wireless nodes with limited processing resources.

The proposed ontology generated a set of classes and properties to represent the heterogeneous network characteristics as shown in Tables 6-1 and 6-2, respectively.

Figure. 6.2 shows the ontology graph of the proposed heterogeneous wireless network in which the classes, subclasses, and properties are shown.

Table 6-1: Ontology classes.

Class name	Parent Class	Description
HetNet	-	Heterogeneous wireless network
Node	HetNet	Wireless and wired nodes
LTENode	Node	Nodes equipped with LTE device
NetNode	Node	Nodes equipped with LTE and IEEE 802.11n
VanetNode	Node	Nodes equipped with IEEE 802.11p
HetCars	VanetNode	Wireless nodes equipped with LTE and IEEE 802.11p
IEEE802.11pCars	VanetNode	Wireless nodes equipped with IEEE 802.11p
RAN	HetNet	Radio access network type
LTENet	RAN	LTE radio access network
Wi-FiNet	RAN	Wi-Fi radio access network
IEEE802.11nNet	Wi-FiNet	Wireless devices of type IEEE 802.11n
IEEE802.11pNet	Wi-FiNet	Wireless devices of type IEEE 802.11p

Table 6-2: Ontology properties.

Property	Description
hasLTELoad	Define the load on the LTE network
hasLTEChannelQuality	Define the channel quality of the LTE network
hasWi-FiSucRate	Wi-Fi network success rate of transmitting data packets
hasWi-FiChannelRate	Wi-Fi network transmission rate
hasLTESW	Strength weight to select LTE; this property is inferred from the rule-base
hasWi-FiWeight	Strength weight to select Wi-Fi network
hasRAND	Decision to select the radio access network
hasNeigh	One-hop neighbours of wireless node; this value is obtained from the routing table
hasShortestPath	Next hop node with the shortest path to the Mesh Gateway; this value is obtained from the routing table

SelectNextHop	Decision of selecting the node as a next hop
hasHops	Defines the number of hops from the node to the Mesh Gateway along the shortest path; this value is obtained from the routing table
hasLCD	Defines the link connectivity duration (LCD) between two neighbouring nodes in VANET

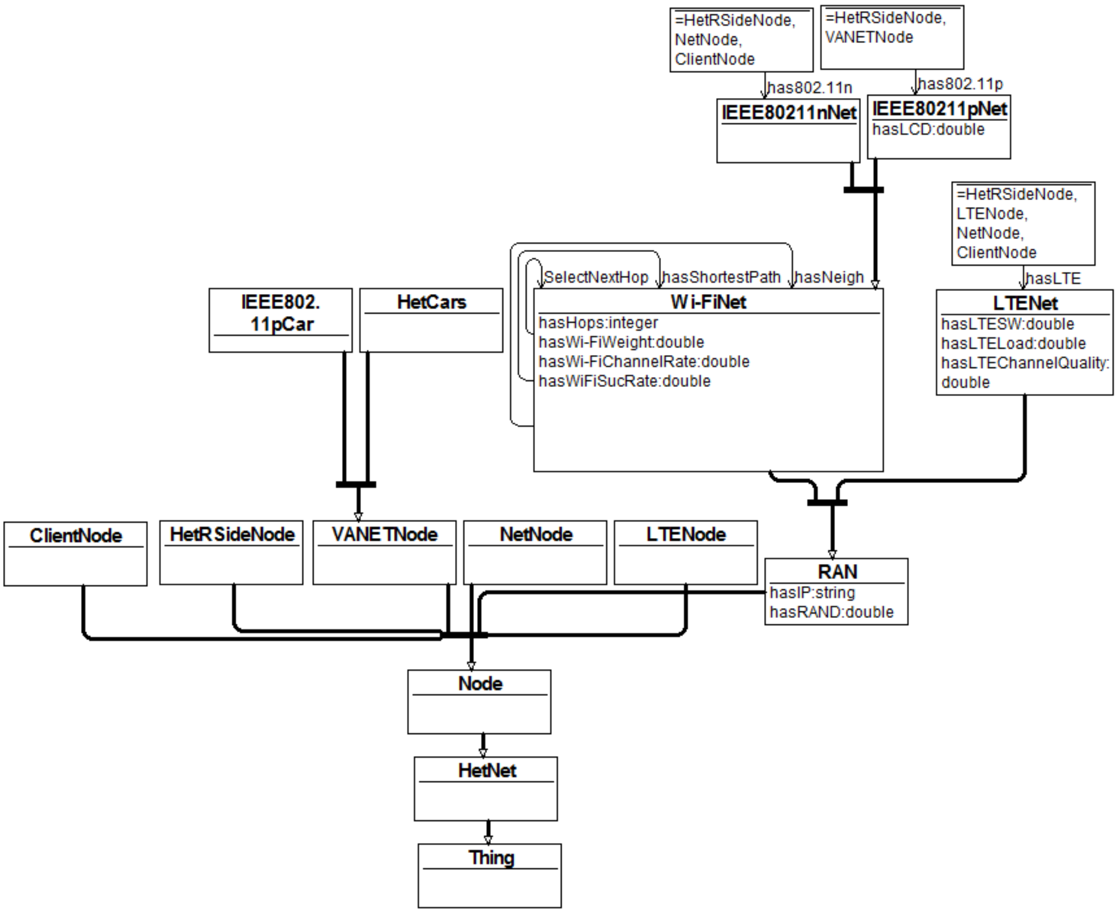

Figure 6-2: Ontology graph of the heterogeneous wireless mesh network.

6.2.2 Fuzzy-based Knowledge Base

The network characteristics and node configuration parameters are stored in the fuzzy-based knowledge base as instances of the heterogeneous network ontology. The QoS parameters of each RAN are transformed from crisp points (x) to fuzzy sets [x, $\mu(x)$] in

U, where μ is the membership function U ϵ [0 − 1]. In this model, the QoS parameters provided by each RAN are fuzzified using predefined membership functions as shown in Figure 6.3 - 6.6. The fuzzification process maps the input value to names and degrees of membership functions.

Each membership function presents a curve that represents the possible degrees for each input value. For example, the input value of LTE load is transformed to the degree in the membership figure according to the coordinate of this value on the curve. These values will be assigned to the ontology property for each RAN. A set of rules uses these fuzzified values to select the transmission technology for the network.

The fuzzification step is performed on the QoS parameters for each transmission technology. The LTE network employs two parameters to estimate the quality of the network. The first parameter is the load on the network, which is calculated based on the number of resource blocks (RBs) (Yang et al. 2013) assigned to each node using the following:

$$LTEL_t^d = \frac{RB_t^d}{RBMax} * 100\%, \tag{6.1}$$

where $LTEL^d_t$ is the load on the LTE network for node d at time t, RB^d_t represents the number of allocated resource blocks for node d at time t, and $RBMax$ is the number of available resource blocks for the LTE cell. $LTEL^d_t$ is mapped to a fuzzy set using the membership function in Figure 6.3. The second parameter for the LTE network is the channel quality indicator (CQI), which is collected by the eNB base station. CQI provides information on the quality of the communication channel, while the eNB selects the appropriate modulation and coding method based on the CQI feedback from the user

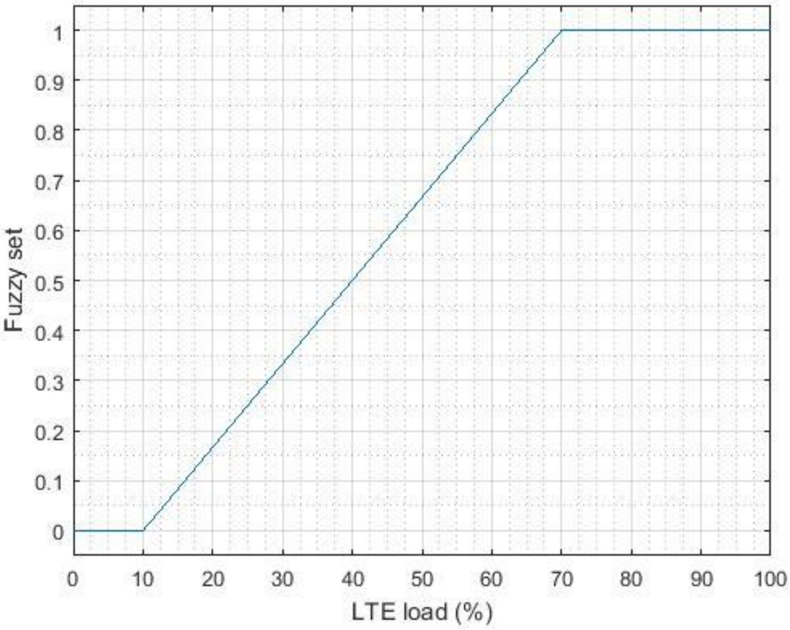

Figure 6-3: LTE load membership function (in %).

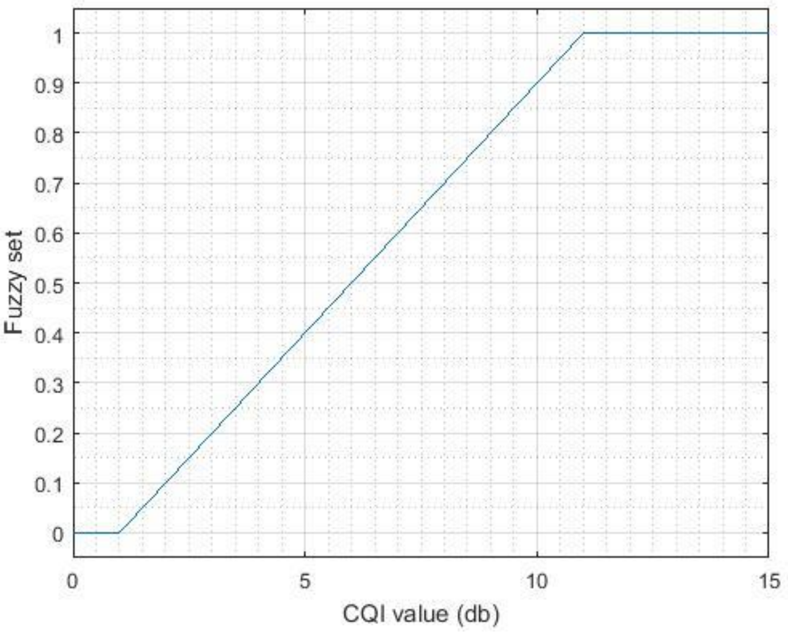

Figure 6-4: CQI membership function (in db).

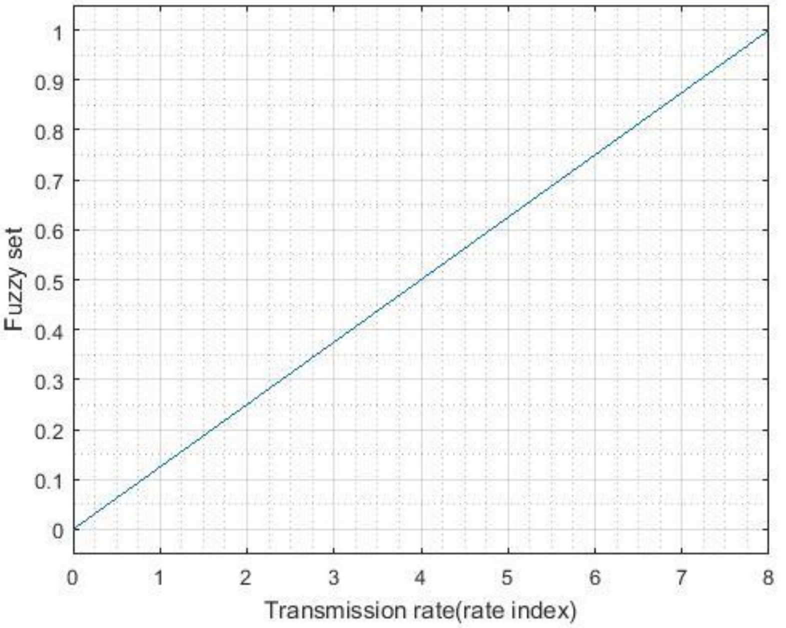

Figure 6-5: Wi-Fi transmission rate membership function (in rate index value).

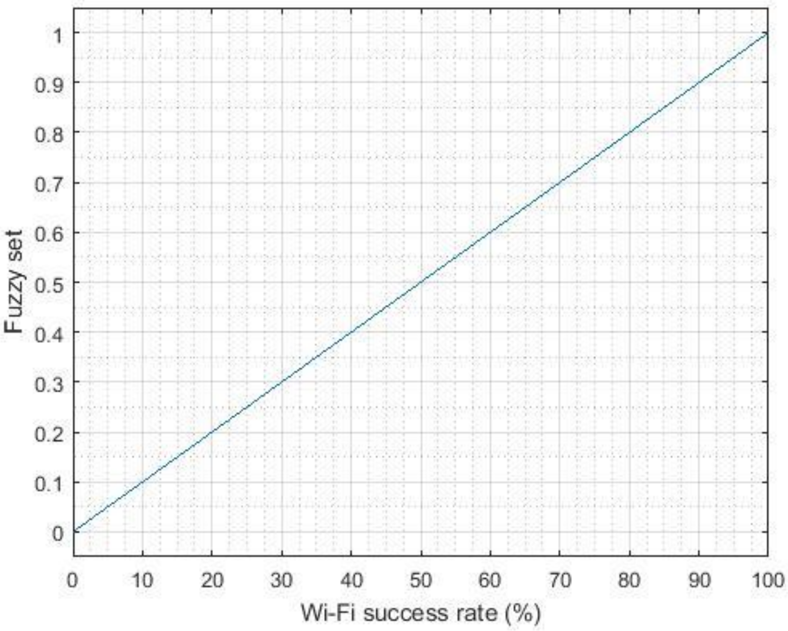

Figure 6-6: The success rate for Wi-Fi device (SRW) membership function (in %).

equipment (UE). In this work, the channel quality value is mapped to the corresponding fuzzy degree in the membership function as shown in Figure 6.4. The CQI information is between 0 and 15, where 15 is a standard value for the best channel quality while 0 means it is out of range.

In this chapter, the rate adaptation algorithm proposed in Chapter 2 is used to measure the link quality. *RARE* employs both the load and the interference to calculate the transmission rate. The node with the highest transmission rate has the best link quality because RARE decreases the transmission rate when the transmission link suffers from interference and high packet loss.

The WMN also uses two parameters to estimate the channel quality, the transmission rate of each node during time slot t_i, and the probability of accessing the channel. The membership function in Figure 6.5 defines eight fuzzy degrees for the transmission rates in IEEE 802.11n (15, 30, 45, 60, 90, 120, 135, and 150 Mbps) and eight fuzzy degrees in IEEE 802.11p (6, 9, 12, 18, 24, 36, 48, and 54 Mbps). The second parameter is the success rate of the Wi-Fi device in accessing the wireless channel on the node, which is estimated using (6-2) (Benslimane and Rachedi 2014).

$$SRW^{d}(t_{i-1}-t_{i})=\frac{STW^{d}(t_{i-1}-t_{i})}{TTW^{d}(t_{i-1}-t_{i})}*100\%, \tag{6.2}$$

where $SRW^d(t_{i-1} - t_i)$ is the success rate for the Wi-Fi device on node *d* since the last update of the transmission rate $(t_{i-1} - t_i)$. STW^d $(t_{i-1} - t_i)$ is the number of successful transmissions for node *d* from the interval of the last rate update. *STW* is calculated by counting the number of received acknowledgments on the Wi-Fi medium access layer (MAC). $TTW^d(t_{i-1} - t_i)$ is the total number of transmissions for the Wi-Fi device on node *d* since the previous transmission rate update.

For the heterogeneous networks using VANET, the LCD (Tabbane et al. 2015) is utilised in selecting the next hop. The link connectivity duration (LCD) metric reflects the lifetime of a communication link between two nodes. Equation (6.3) (Tabbane et al. 2015) is employed to calculate the LCD.

$$LCD_{i,j} = \frac{\sqrt{(\alpha^2+\gamma^2)\mathrm{R}^2-(\alpha\delta-\beta\gamma)^2}-(\alpha\beta+\gamma\delta)}{\alpha^2+\gamma^2}, \tag{6.3}$$

where $\alpha = v_i \cos \theta_i - v_j \cos \theta_j$, $\gamma = v_i \sin \theta_i - v_j \sin \theta_j$, and v_i and v_j are the velocities of moving cars for nodes *i* and *j*, respectively. θ_i and θ_j are the inclination with *x*-axes ($0 < \theta_i, \theta_j < 2\Pi$). $\beta = xi - xj$ and $\delta = yi - yj$, where x_i, y_i and x_j, y_j are the Cartesian coordinates of nodes *i* and *j*. R is the transmission range of the IEEE 802.11p. The LCD parameter is calculated for adjacent nodes to calculate the lifetime of the wireless link. Figure 6.7 shows an example of an ontology instance for a NetNode using fuzzy logic to weight each RAN parameter. The instances of the ontology are stored in the knowledge base using fuzzy member functions defined in Figure. 6.3–6.6. For example, the value of the hasLTELoad property is 0.55, which is the fuzzy membership value of the LTE load calculated using Figure 6.3, where 0.55 corresponds to 45% of the available resources being allocated to the node. A similar method is applied to compute hasLTEChannelQuality, hasWiFiChannelRate, and hasWi-FiSuccessRate using the membership functions in Figure 6.4, 6.5, and 6.6, respectively.

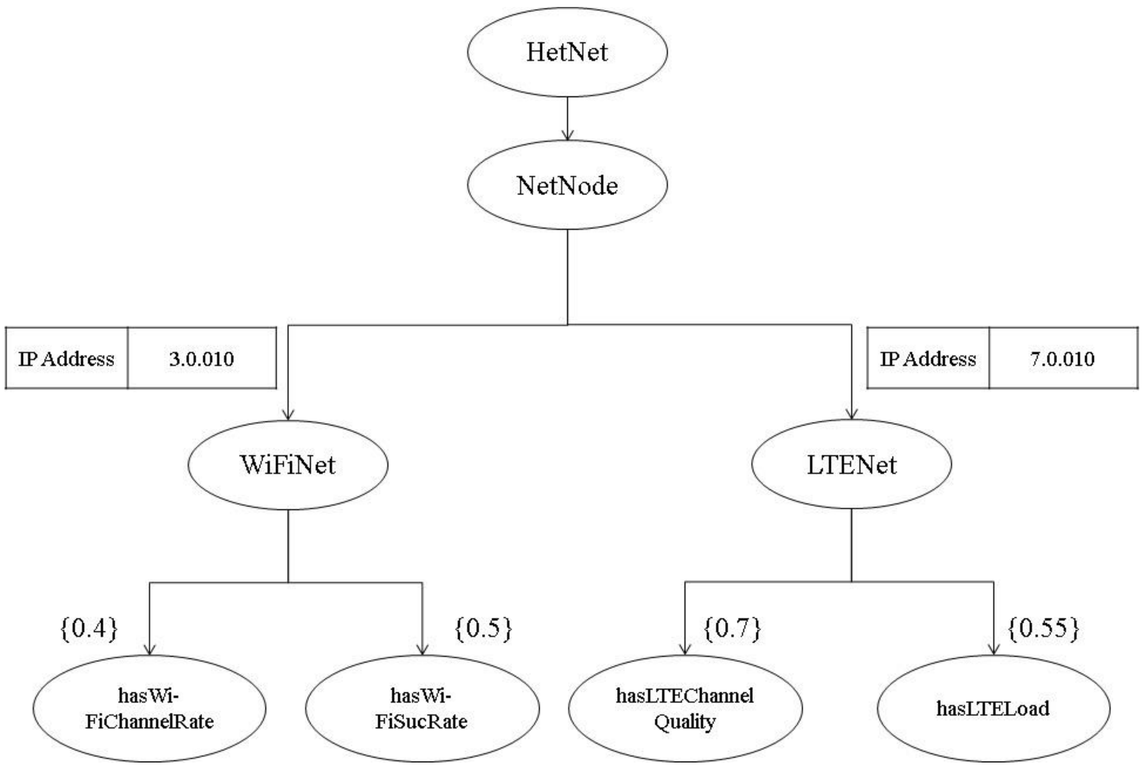

Figure 6-7: Graph of knowledge base instance for NetNode.

6.2.3 **Semantic Rule-base and Fuzzy-based Reasoning System**

This section defines a set of rules that were created based on the classes, subclasses, and relationships in the ontology. The fuzzy-based reasoning system uses these rules, in addition to the instances of the ontology in the knowledge base, to control the different network architectures and obtain the best RAN on the node for packet transmission. The reasoning system is developed to control the three networks (WMN, VANET, and LTE) and each network type uses a different RAN (IEEE 802.11n, IEEE 802.11p, and LTE).

The fuzzy-based reasoning system uses a set of rules to obtain the RAN with the best link quality. The rule base is responsible for checking whether the ClientNodes accept other nodes packets to relay. The users of the ClientNodes can set them to participate in the network infrastructure or not. By participating in the network infrastructure, the ClientNodes can reduce the load on the heterogeneous network and the user could obtain some benefits, such as getting a discount.

The fuzzified values obtained from the QoS parameters of each RAN are employed to evaluate the set of rules using the fuzzy-based reasoning system. The proposed fuzzy-based reasoner utilises the rule base and the instances of the ontology in the knowledge base to infer the best RAN. The rules, which are defined below, were formed in semantic web rule language (SWRL) (W3C 2004). The Pellet reasoner (Sirin et al. 2007) was used to check the consistency of the ontology.

Rules: Select the Radio Access Network

$LTENet(?IP) \wedge WiFiNet(?IP) \wedge hasLTELoad(?IP, ?FLL) \wedge$
$\quad hasLTEChannelQuality(?IP, ?FLC) \rightarrow hasLTEQ(?IP, ?LSW)$

$LTENet(?IP) \wedge WiFiNet(?IP) \wedge hasWiFiSucRate(?IP, ?FWS) \wedge$
$\quad hasWiFiChannelRate(?IP, ?FWC) \rightarrow hasWiFiWeight(?IP, ?WSW)$

$centroid\big(hasLTEWeight(?IP, ?LTEW), hasWiFiWeight(?IP, ?WiFiW)\big) \rightarrow$
$\quad hasRAND(?IP, ?RAND)$

Rules: Select Next hop for ClientNodes and NetNodes

$hasNeigh\ (?IP, ?IP1) \wedge NetNode(?IP1) \wedge$
$\quad hasShortestPath(?IP, ?IP1) \rightarrow SelectNextHop(?IP, ?IP1)$

$hasNeigh\ (?IP, ?\ IP1) \wedge ClientNode(IP1) \wedge$
$\quad hasShortestPath(?IP, ?IP1) \rightarrow SelectNextHop(?IP, ?IP1)$

$$hasNeigh\ (?IP, ?\ IP1) \wedge NetNode(?IP1) \wedge$$
$$hasShortestPath(?IP, ?IP1) \rightarrow SelectNextHop(?IP, ?IP1)$$

$$hasNigh\ (?IP, ?IP1) \wedge hasNeigh\ (?IP, ?IP2) \wedge NetNode(?IP1) \wedge ClientNode(?IP2) \wedge$$
$$swrlb: equal(hasHopes(?IP1, ?Hops), hasHopes(?IP2, ?Hopes)) \wedge$$
$$hasShortestPath(?IP, ?IP1) \wedge$$
$$swrlb: greaterThan(\mathrm{hasWiFiWeight}(?IP1, ?WSW), \mathrm{hasWiFiWeight}(?IP2, ?WSW)) \rightarrow$$
$$SelectNextHop(?IP, ?IP1)$$

$$hasNigh\ (?IP, ?IP1) \wedge hasNeigh\ (?IP, ?\ IP2) \wedge NetNode(?IP1) \wedge ClientNode(?IP2) \wedge$$
$$swrlb: equal(hasHopes(?IP1, ?Hopes), hasHopes(?IP2, ?Hopes)) \wedge$$
$$hasShortestPath(?IP, ?IP1) \wedge$$
$$swrlb: equal(hasWiFiWeight(?IP1, ?WSW), hasWiFiWeight(?IP2, ?WSW)) \rightarrow$$
$$SelectNextHop(?IP, ?IP1)$$

where *IP*, *IP*1, and *IP*2 represent the Internet protocol (IP) addresses of the different nodes, *FLL* is the fuzzy set of the LTE load, and *FLC* is the fuzzy set of the LTE channel quality. *LSW* is the strength weight for selecting the LTE device and is computed from the minimum of *FLL* and *FLC* (the fuzzy "and" operator). *FWS* is the fuzzy set of the Wi-Fi success rate; this value is obtained from the MAC layer of the IEEE 802.11(n or p) device by counting the number of received acknowledgments using equation (6.2). *FWC* is the fuzzy membership degree for the Wi-Fi channel transmission rate, and the value is obtained from the *RARE* rate adaptation algorithm. The minimum of *FWC* and *FWS* (the fuzzy "and" operator) represents the strength weight to select the Wi-Fi device (*WSW*).

In the VANET heterogeneous network scenario, three types of nodes are included in the heterogeneous network. The first two types are vehicles equipped with both IEEE 802.11p and LTE (HetCars) and vehicles equipped with only IEEE 802.11p (802.11pCars). These moving nodes are sending data to the roadside units (HetRSide). This study considers the V2I communication. The rule base for the VANET heterogeneous network is shown below.

Rules: Select next hop for HetCars and 802.11pCars

$hasNeigh\ (?IP, ?IP1) \wedge RoadSideNode(?IP1) \wedge$

$swrlb: greaterThan(hasLCD(?IP1, ?LCD), ?LCDthr) \wedge$

$hasShortestPath(?IP, ?IP1) \rightarrow SelectNextHop(?IP, ?IP1)$

$hasNeigh\ (?IP, ?IP1) \wedge VANETNode(?IP1) \wedge$

$swrlb: greaterThan(hasLCD(?IP1, ?LCD), ?LCDthr) \wedge$

$hasShortestPath(?IP, ?IP1) \rightarrow SelectNextHop(?IP, ?IP1)$

$hasNigh\ (?IP, ?\ IP1) \wedge hasNeigh\ (IP, IP2) \wedge VANETNode(?IP1) \wedge$

$VANETNode(?IP2) \wedge swrlb: greaterThan(hasLCD(?IP1, ?LCD), ?LCDthr) \wedge$

$swrlb: greaterThan(hasLCD(?IP2, ?LCD), ?LCDthr) \wedge$

$swrlb: equal\big(hasHops(?IP1, ?Hops), hasHops(?IP2, ?Hops)\big) \wedge$

$swrlb: greaterThan\big(hasWiFiWeight(IP1, WSW), hasWiFiWeight(IP2, WSW)\big) \wedge$

$hasShortestPath(?IP, ?IP1) \rightarrow SelectNextHop(?IP, ?IP1)$

$hasNigh\ (?IP, ?\ IP1) \wedge hasNeigh\ (IP, IP2) \wedge VANETNode(?IP1) \wedge$

$RoadSideNode(?IP2) \wedge swrlb: greaterThan(hasLCD(?IP1, ?LCD), ?LCDthr) \wedge$

$swrlb: greaterThan(hasLCD(?IP2, ?LCD), ?LCDthr) \wedge$

$swrlb{:}\, equal\big(hasHops(?\, IP1, ?\, Hops), hasHops(?\, IP2, Hops)\big) \wedge$

$hasShortestPath(?\, IP, ?\, IP1) \rightarrow SelectNextHop(?\, IP, ?\, IP1)$

$hasNigh\ (?\, IP, ?\ \ IP1) \wedge hasNeigh\ (IP, IP2) \wedge RoadSideNode(?\, IP1) \wedge$

$RoadSideNode(?\, IP2) \wedge RoadSideNode(?\, IP2) \wedge$

$swrlb{:}\, greaterThan(hasLCD(?\, IP1, ?\, LCD), ?\, LCDthr) \wedge$

$swrlb{:}\, greaterThan(hasLCD(?\, IP2, ?\, LCD), ?\, LCDthr) \wedge$

$swrlb{:}\, equal\big(hasHops(?\, IP1, ?\, Hops), hasHops(?\, IP2, ?\, Hops)\big) \wedge$

$hasShortestPath(?\, IP, ?\, IP1) \wedge$

$swrlb{:}\, greaterThan\big(hasWiFiWeight(IP1, WSW), hasWiFiWeight(IP2, WSW)\big) \rightarrow$

$SelectNextHop(?\, IP, ?\, IP1)$

Rules: Select next hop for HetRSide

$hasNeigh\ (?\, IP, ?\, IP1) \wedge NetNode(?\, IP1) \wedge$

$swrlb{:}\, greaterThan(hasLCD(?\, IP1, ?\, LCD), ?\, LCDthr) \wedge$

$hasShortestPath(?\, IP, ?\, IP1) \rightarrow SelectNextHop(?\, IP, ?\, IP1)$

$hasNeigh\ (?\, IP, ?\ \ IP1) \wedge ClientNode(IP1) \wedge$

$swrlb{:}\, greaterThan(hasLCD(?\, IP1, ?\, LCD), ?\, LCDthr) \wedge$

$hasShortestPath(IP, IP1) \rightarrow SelectNextHop(?\, IP, IP1)$

$hasNigh\ (?\, IP, ?\ \ IP1) \wedge hasNeigh\ (IP, IP2) \wedge NetNode(?\, IP1) \wedge RoadNode(?\, IP2) \wedge$

$swrlb{:}\, greaterThan(hasLCD(?\, IP1, ?\, LCD), ?\, LCDthr) \wedge$

$swrlb{:}\, greaterThan(hasLCD(?\, IP2, ?\, LCD), ?\, LCDthr) \wedge$

$swrlb{:}\, equal\big(hasHops(?\, IP1, ?\, Hops), hasHops(?\, IP2, ?\, Hops)\big) \wedge$

$hasShortestPath(?\, IP, ?\, IP1) \rightarrow SelectNextHop(?\, IP, ?\, IP1)$

$$hasNigh\ (?\,IP, ?\ \ IP1) \wedge hasNeigh\ (IP, IP2) \wedge RoadSideNode(?\,IP1) \wedge$$
$$RoadSideNode(?\,IP2) \wedge swrlb{:}\, greaterThan(hasLCD(?\,IP1, ?\,LCD), ?\,LCDthr) \wedge$$
$$swrlb{:}\, greaterThan(hasLCD(?\,IP2, ?\,LCD), ?\,LCDthr) \wedge$$
$$swrlb{:}\, equal\big(hasHops(?\,IP1, ?\,Hops), hasHops(?\,IP2, ?\,Hops)\big) \wedge$$
$$hasShortestPath(?\,IP, ?\,IP1) \wedge$$
$$swrlb{:}\, greaterThan\big(hasWiFiWeight(IP1, WSW), hasWiFiWeight(IP2, WSW)\big) \rightarrow$$
$$SelectNextHop(?\,IP, ?\,IP1)$$

$$hasNigh\ (?\,IP, ?\,IP1) \wedge hasNeigh\ (?\,IP, ?\,IP2) \wedge ClientNode(?\,IP1) \wedge ClientNode(?\,IP2) \wedge$$
$$swrlb{:}\, greaterThan(hasLCD(?\,IP1, ?\,LCD), ?\,LCDthr) \wedge$$
$$swrlb{:}\, greaterThan(hasLCD(?\,IP2, ?\,LCD), ?\,LCDthr) \wedge$$
$$swrlb{:}\, equal\big(hasHops(?\,IP1, ?\,Hops), hasHops(?\,IP2, ?\,Hops)\big) \wedge$$
$$hasShortestPath(?\,IP, ?\,IP1) \wedge$$
$$swrlb{:}\, greaterThan\big(hasWiFiWeight(?\,IP1, ?\,WSW), hasWiFiWeight(?\,IP2, ?\,WSW)\big) \wedge$$
$$\rightarrow SelectNextHop(?\,IP, ?\,IP2)$$

$$hasNigh\ (?\,IP, ?\ \ IP1) \wedge hasNeigh\ (?\,IP, ?\,IP2) \wedge ClientNode(?\,IP1) \wedge RoadNode(?\,IP2) \wedge$$
$$swrlb{:}\, greaterThan(hasLCD(?\,IP1, ?\,LCD), ?\,LCDthr) \wedge$$
$$swrlb{:}\, greaterThan(hasLCD(?\,IP2, ?\,LCD), ?\,LCDthr) \wedge$$
$$swrlb{:}\, equal\big(hasHops(?\,IP1, ?\,Hops), hasHops(?\,IP2, ?\,Hops)\big) \wedge$$
$$hasShortestPath(?\,IP, ?\,IP1) \rightarrow SelectNextHop(?\,IP, ?\,IP2)$$

The HetCars nodes use *Rules: Select the RAN* to select either the LTE or the IEEE 802.11p. If the LTE is selected, then the data are directly transmitted through the LTE network. For HetCars nodes that select IEEE 802.11p, as well as for 802.11pCars, the *Rules: Select Next Hop for HetCars and 802.11pCars* are used to choose the next hop node to the Mesh Gateway. The next hop node could be HetCars, 802.11pCars, or HetRSide. The node selects the next hop with the LCD that is greater than LCD_{thr} (in this study, LCD_{thr} is equal to 30 s) that has the shortest path to the Mesh Gateway. If more than one node has the same hop count, then the next node is selected based on the node type. HetRSide nodes are selected before HetCars and 802.11pCars, and HetCars nodes are selected before 802.11pCars.

Figure 6.8 shows a flowchart of the Fuzz-Onto reasoning. The process of selecting a transmission technology starts if the node type is of the class HetNet. Then LSW and WSW are calculated. LSW is the weight of the LTE device, and it is the result of a fuzzy "and" operation of a fuzzy set of the LTE load (FLL) and a fuzzy set of the LTE channel quality (FLC), which are obtained in Figures 6.3 and 6.4, respectively. Similarly, the weight of the Wi-Fi device (WSW) is calculated using a fuzzy "and" operation of a fuzzy set of the Wi-Fi success rate (FWS) and a fuzzy set of the Wi-Fi channel transmission rate (FWC), which are computed in Figures 6.5 and 6.6, respectively. Mamdani fuzzy inference is then used to select the RAN. Mamdani fuzzy inference consists of three main modules: the fuzzifier, the rule base and the defuzzifier. The fuzzifier obtains the QoS parameters for each RAN and stores the fuzzy set as an instance of the ontology in the knowledge base. The fuzzified values are used to evaluate the rule base to obtain the radio access network decision (RAND). The final step is defuzzification, which is the process of mapping the output fuzzy set back to a crisp value. The most commonly used method is the centroid method, which was developed by Sugeno in 1985. The only problem with this method is that it is difficult to compute in complex membership functions. However, in this work, the membership functions have a simple trapezoid shape. The centroid defuzzification is calculated using the following equation (Sugeno 1985):

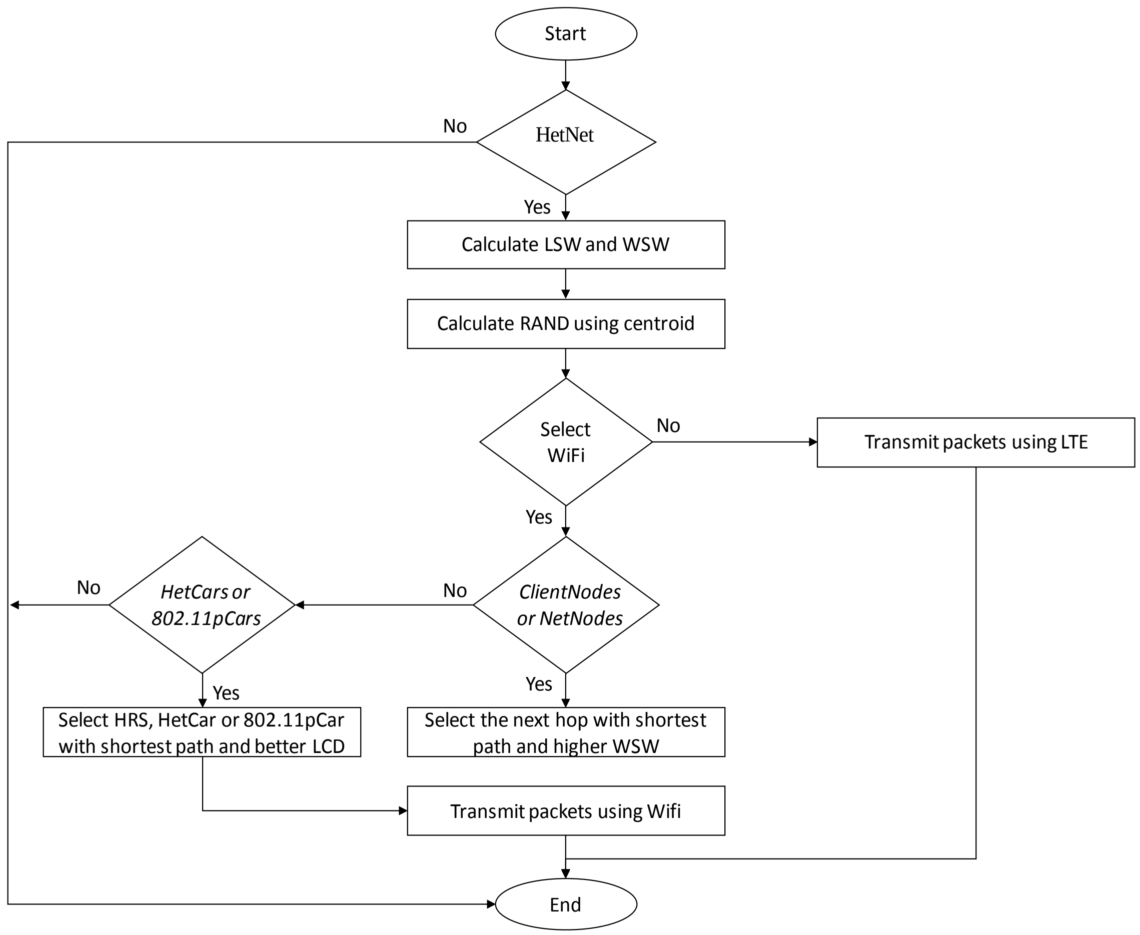

Figure 6-8: FuzzOnto reasoning flowchart

$$RAND = \frac{\int \mu_i(x)xdx}{\int \mu_i(x)dx}, \tag{6.4}$$

where *RAND* is the defuzzified value of the output fuzzy set and *μ* is the aggregated membership function for the output value. The value of *RAND* is used to select the transmission technology. If LTE is selected, the traffic demand is transmitted directly to the eNB base station. If Wi-Fi is selected, *Rules: Select Next Hop for ClientNodes and NetNodes* are used to select the next node to forward the traffic demands. These rules determine the shortest path to the mesh gateway, and they are used to choose the net node or client node with the shortest path in terms of hop count. If two nodes have the same number of hops to the mesh gateway, then the node with the highest WSW is selected to forward the packets. If two nodes have the same WSW, then net nodes are selected over client nodes to reduce the load on the latter.

If the node is of type HetCar or 802.11pCar, the algorithm selects the next hop with the shortest path to the mesh gateway and has an LCD greater than LCD_{thr} (in this study, LCD_{thr} is equal to 30 s). If more than one node has the same hop count, then the next node is selected based on the node type. HetRSide nodes are selected before HetCars and 802.11pCars, and HetCars nodes are selected before 802.11pCars.

In the VANET heterogeneous network scenario, three types of nodes are included in the heterogeneous network. The first two types are vehicles equipped with both IEEE 802.11p and LTE (HetCars) and vehicles equipped with only IEEE 802.11p (802.11pCars). These moving nodes send data to the roadside units (HetRSide). This study considers the V2I communication.

6.3 Performance Evaluation

For this study, the heterogeneous WMN using the proposed cognitive network framework was evaluated using Network Simulator version 3 (ns-3) (ns-3 n.d.), which is a widely used simulator for networking systems. The LENA module (Baldo et al. 2011) was employed by the ns-3 simulator to simulate the LTE network. The proposed cognitive network framework, called FuzzOnto, was compared in terms of throughput and packet delivery fraction (PDF) with LTE-only network, Wi-Fi-only network, and a number of networks that used different wireless technologies. These networks are listed below:

- Balance: This network distributes the traffic evenly between the LTE and IEEE 802.11n wireless networks;
- Rand: This network randomly selects the transmission technology;
- VH: This wireless network performs vertical handover between the LTE and Wi-Fi networks; it consists of ClientNodes and WMN that uses the Wi-Fi network, and the client can choose between sending through the LTE or the WMN as two separate networks; and
- Learning: This heterogeneous network, proposed in Chapter 5 uses reinforcement learning, but does not employ fuzzy logic to represent the QoS parameters of the networks.

In the VANET network, VanetMobiSim 1.1 (VanetMobiSim) was used to simulate vehicle mobility in the VANET heterogeneous WMN. The bandwidth in the LTE network is represented by the total number of RBs available for the user equipment in the network. In this work, 100 and 75 RB were used in FuzzOnto compared with 100 RB that are used in benchmark networks.

6.3.1 Urban Heterogeneous Network

This scenario involved a random number of ClientNodes distributed in a 1000 m^2 area, three eNB base stations, and 100 NetNodes that formed the backbone of the heterogeneous network. Three different scenarios were used to evaluate the proposed network. In each scenario, 30 ClientNodes were randomly distributed, while different loads were applied to the network (low, medium, and high). The simulation results for each scenario showed that the heterogeneous network that used the proposed cognitive network framework outperformed the benchmark networks in terms of throughput and PDF. Figure 6.8 through 6.13 show the network performance for the FuzzOnto network compared with the benchmark networks. Box and whisker graphs are employed to visualise the results. Each chart has four quartiles; the lower box shows the results that were less than the median while the upper box represents the results that were greater than the median. The upper and lower whiskers represent the highest and lowest values of the results.

The results indicate that FuzzOnto performed better when the load on the network was high. In Figure 6.8, the traffic demands were not high, and FuzzOnto did not show a significant improvement in throughput compared with the LTE, Wi-Fi, Learning, Balance, and Rand networks. In Figure 6.9 and 6.10, the load was higher, and the results indicate that FuzzOnto performed better than the benchmark networks. For instance, in Figure 6.9, FuzzOnto achieved average throughput with up to 46% higher than the other networks when the median of the results was compared. The PDF for the urban heterogeneous network is shown in Figure 6.11-6.13; the results indicate that FuzzOnto outperformed the benchmark networks. For example, Figure 6.13 shows that 50% of the PDF results for the FuzzOnto network were between 0.3 and 0.4 while the other networks performed lower than 0.34.

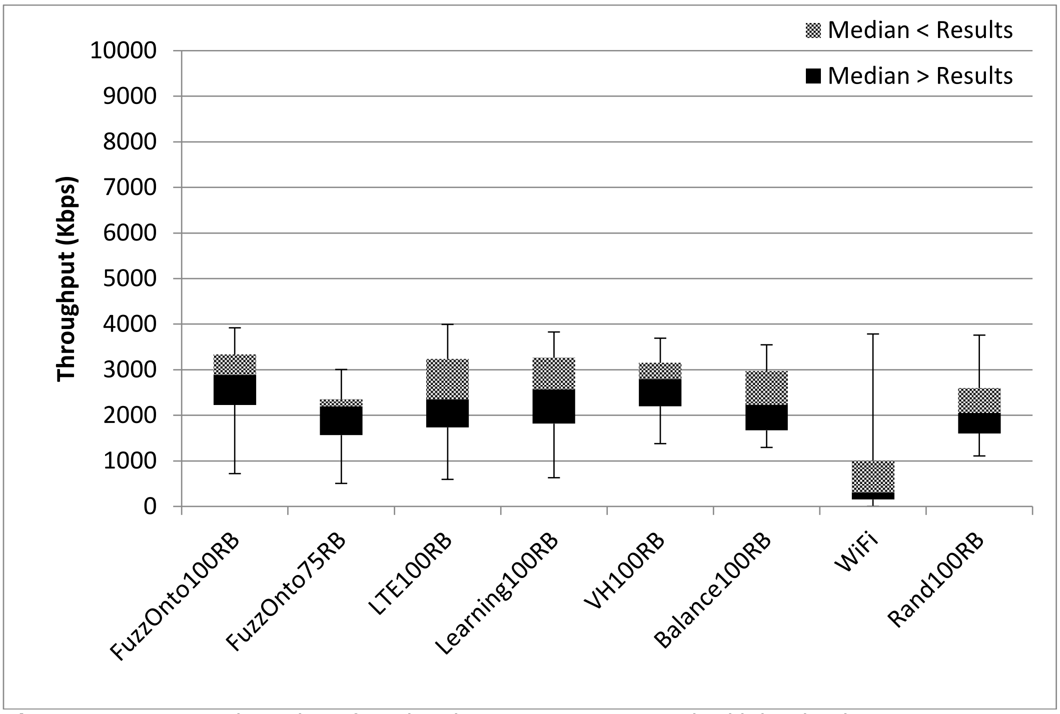

Figure 6-9: Average throughput for urban heterogeneous network with low load.

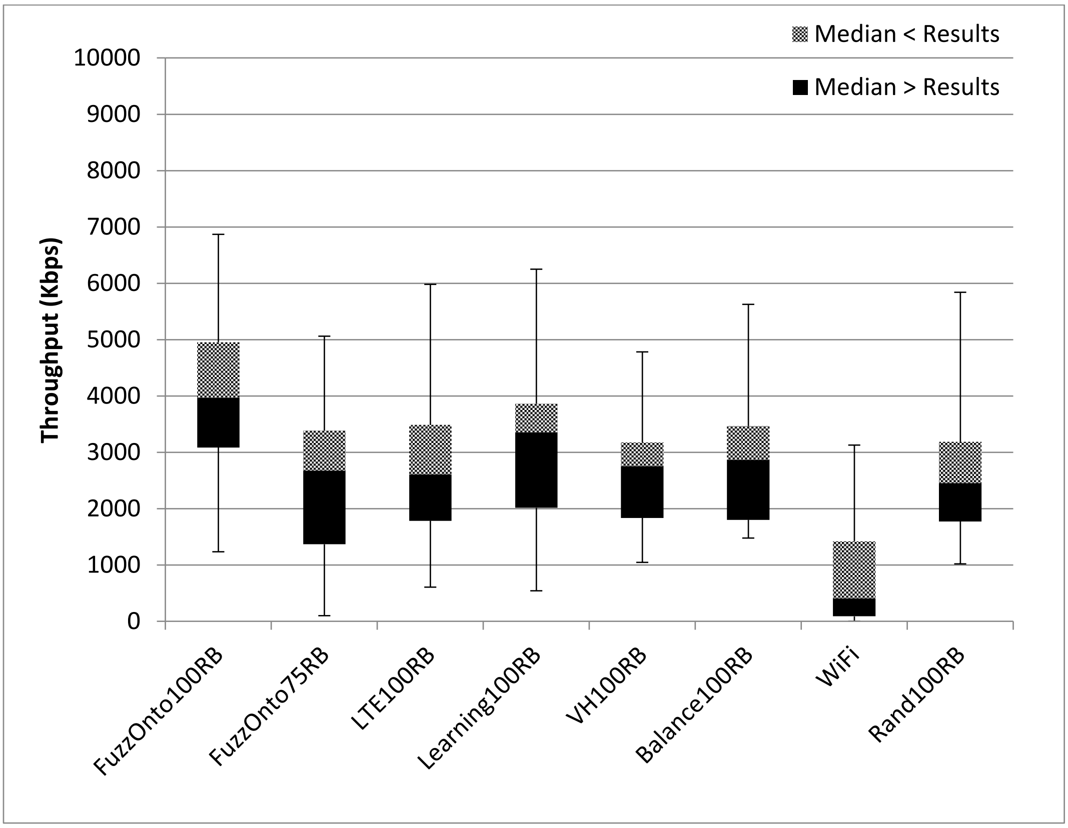

Figure 6-10: Average throughput for urban heterogeneous network with medium load.

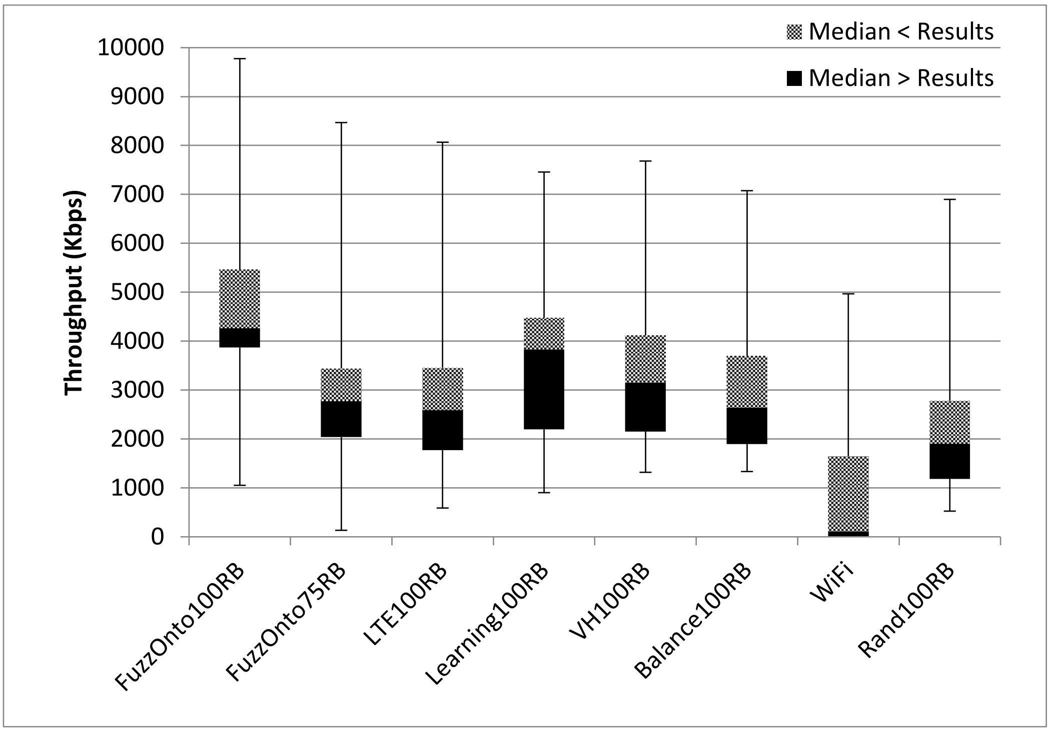

Figure 6-11: Average throughput for urban heterogeneous network with high load.

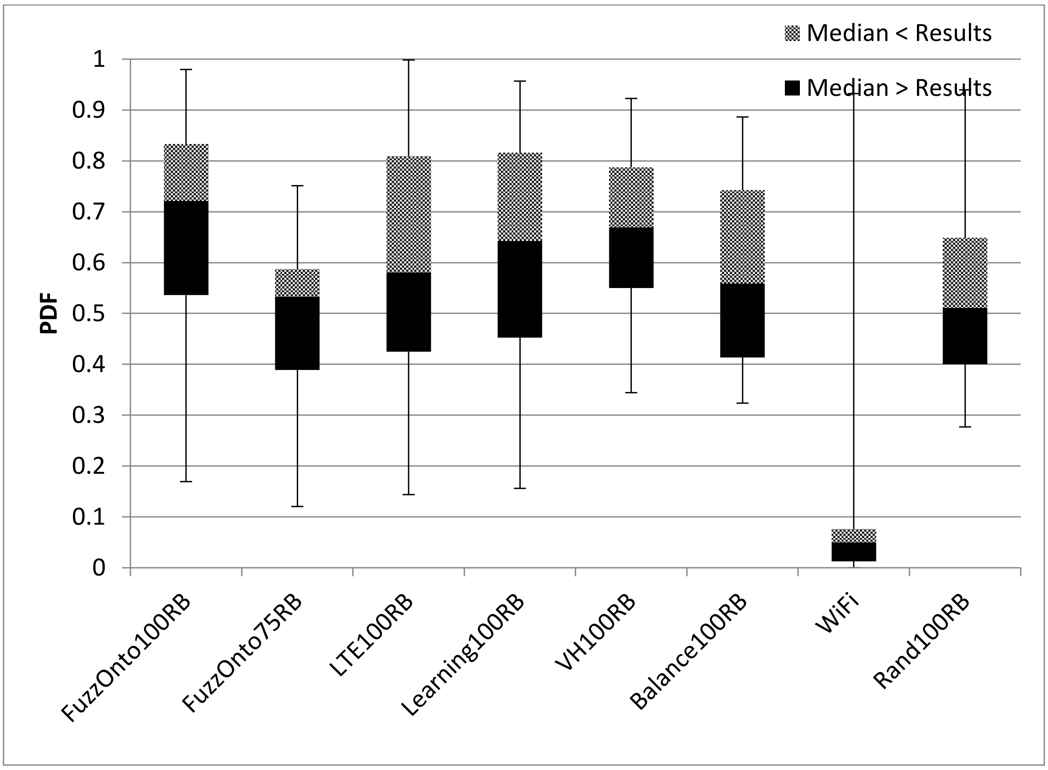

Figure 6-12: Packet delivery fraction of urban heterogeneous network with low load.

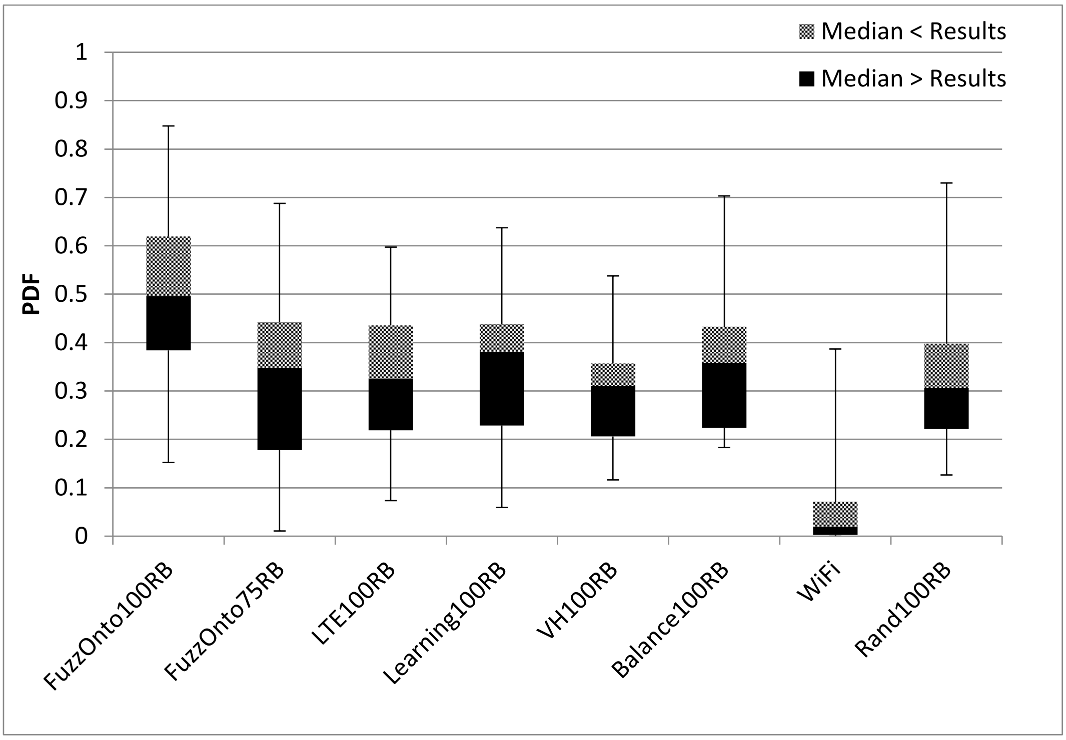

Figure 6-13: Packet delivery fraction of urban heterogeneous network with medium load.

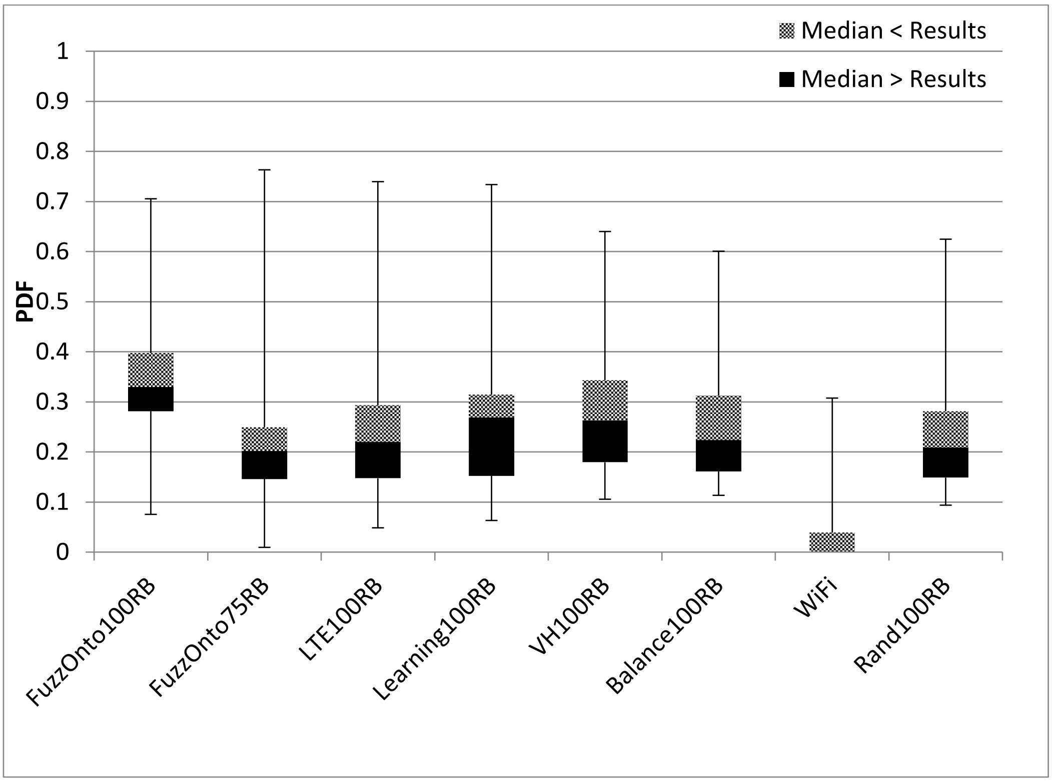

Figure 6-14: Packet delivery fraction of urban heterogeneous network with high load.

6.3.2 **VANET Heterogeneous Network**

In the VANET heterogeneous network, the simulation scenario considered a multi-lane highway and used the VanetMobiSim 1.1 mobility simulation tool to simulate vehicle mobility. The ns-3 simulator used the mobility traces generated by VanetMobiSim 1.1 to simulate the heterogeneous network. Each vehicle was equipped with a global positioning system (GPS) receiver and, therefore, it was possible to determine the position and velocity of each vehicle.

The proposed cognitive network was compared in terms of throughput and PDF with the same benchmark networks used in the urban heterogeneous network scenario. Figure 6.14 through 6.19 show the network performance in terms of throughput and PDF.

Similar to the urban heterogeneous network, the FuzzOnto network performed better when the load on the network was high. Figure 6.16 shows that the median achieved throughput for FuzzOnto with a LTE bandwidth of 100 RB was around 2.6 Mbps, while the LTE network achieved around 1.2 Mbps. Even when the FuzzOnto used only 75 RB, it outperformed the LTE network with 100 RB by about 80%. Finally, the FuzzOnto network achieved an average throughput with an increase of more than 40% compared with the other networks. FuzzOnto also achieved a higher PDF compared with the other networks. For example, in Figure 6.18, the FuzzOnto network achieved a PDF around 0.45 while the best benchmark network achieved a PDF around 0.29.

To verify that the proposed model was significantly improving the network throughput, ANOVA statistical test was performed on each scenario. This test verified that the difference between the results in each scenario was systematic. Equation (6.5) (Scheffe 1959) was used to check whether the results were statistically different.

$$F > F_{Crit,} \tag{6.5}$$

where F is the ANOVA test statistic and F_{Crit} is the critical value obtained from the F-distribution table. Another parameter in the ANOVA test is the probability (p) of having the improvement where the preferred value is < 0.05. To verify that the heterogeneous network employing FuzzOnto produced better throughput, Fisher's least significant difference (LSD) test was performed on the results from each network. The average throughput of each network type (LTE_{avr}, $FuzzOnto_{avr}$, $Rand_{avr}$, VH_{avr}, $Balance_{avr}$, and $Wi\text{-}Fi_{avr}$) was calculated and if $| FuzzOnto_{avr} - LTE_{avr} | > LCD$, then the two averages were statistically different. Table 6-3 and 6-4 show the ANOVA and LCD results for each scenario.

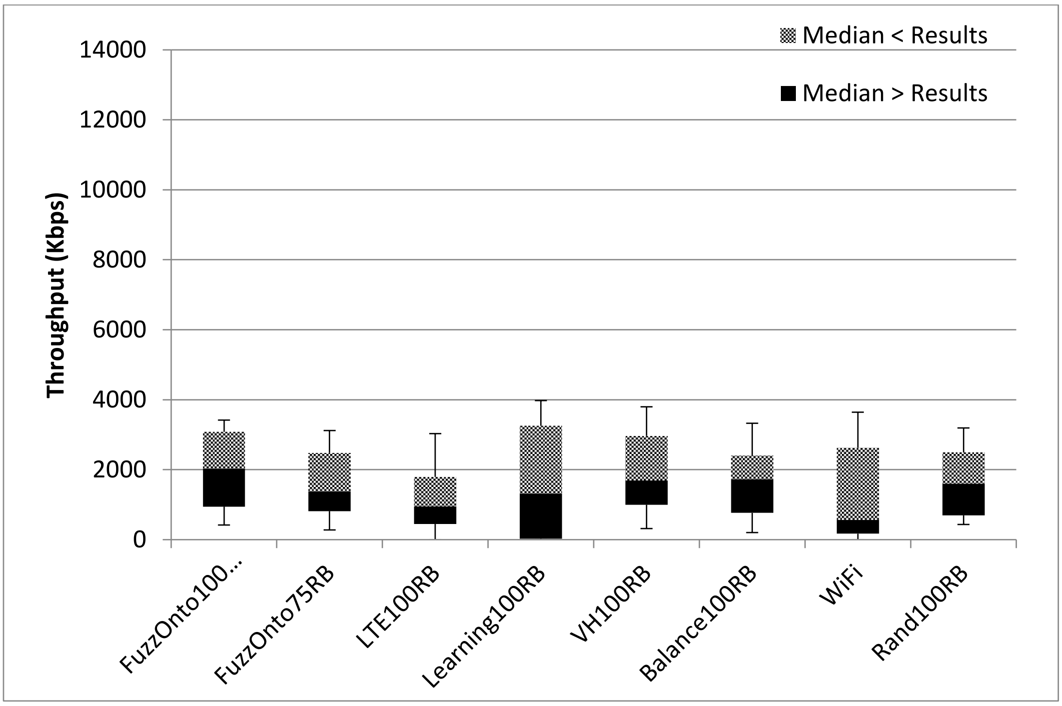

Figure 6-15: Average throughput for VANET heterogeneous network with low load.

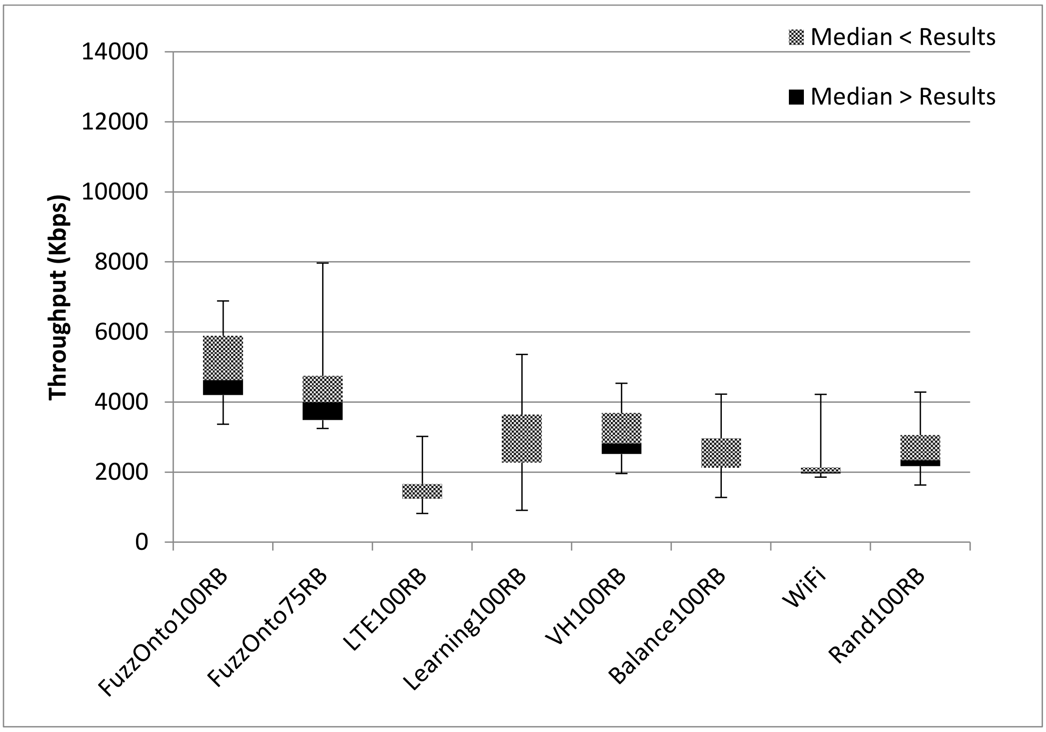

Figure 6-16: Average throughput for VANET heterogeneous network with medium load.

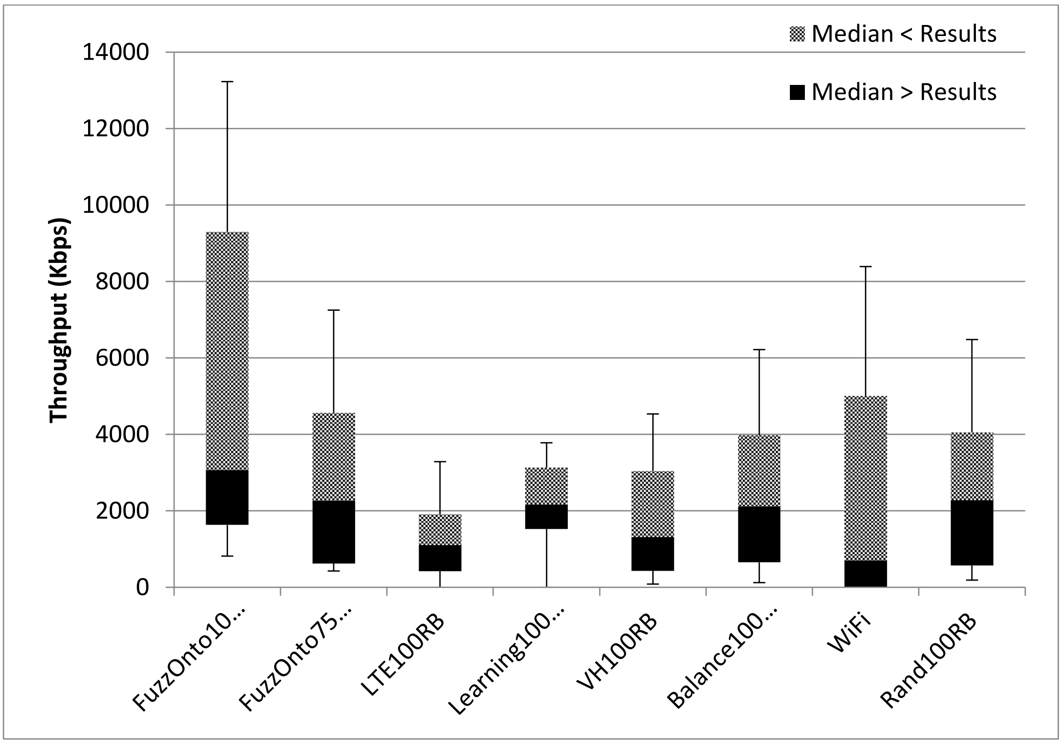

Figure 6-17: Average throughput for VANET heterogeneous network with high load.

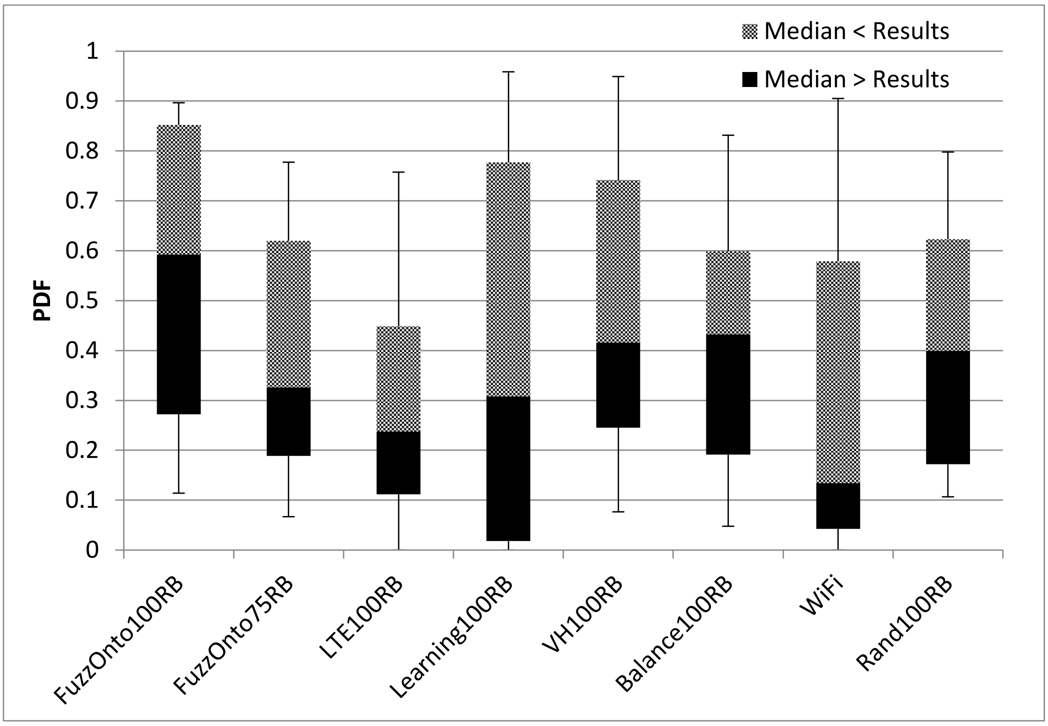

Figure 6-18: Packet delivery fraction for VANET heterogeneous network with low load.

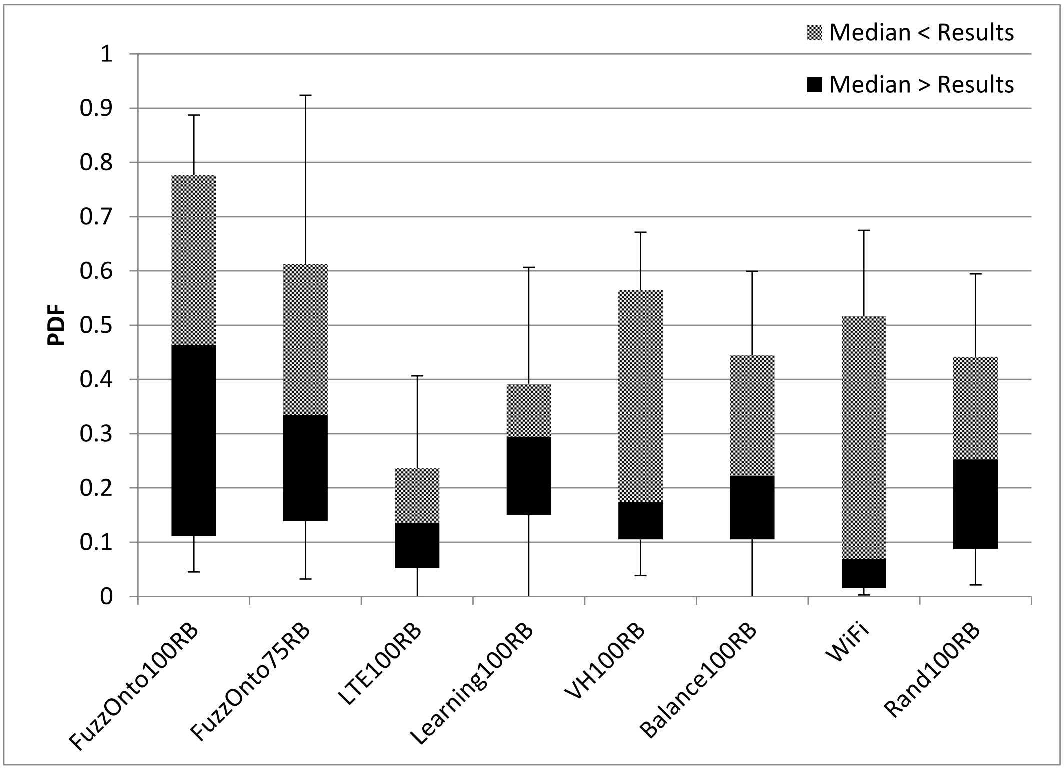

Figure 6-19: Packet delivery fraction for VANET heterogeneous network with medium load.

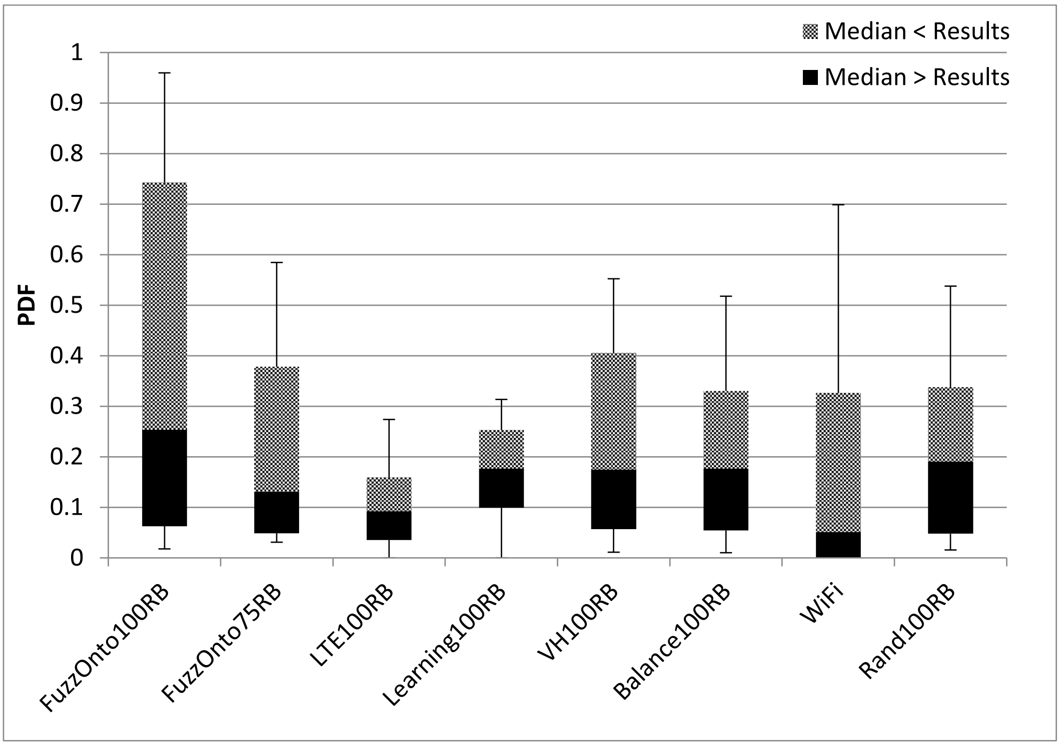

Figure 6-20: Packet delivery fraction for VANET heterogeneous network with high load.

The results of the ANOVA test showed that the throughput results of each network were not obtained by pure chance since p was smaller than 0.001, and the LSD results proved that the throughput results were statistically different.

Table 6-3: ANOVA test results.

Network Scenario	***F***	F_{crit}	***p***
Urban Low Load	11.5	2	$p < 0.001$
Urban Medium Load	8.83	2	$p < 0.001$
Urban High Load	7.79	2	$p < 0.001$
VANET Low Load	1.3	2	$p < 0.001$
VANET Medium Load	3.8	2	$p < 0.001$
VANET High Load	5.1	2	$p < 0.001$

Table 6-4: LSD results.

Network Scenario	Throughput Average for the Networks (Kbps)							LSD
	Onto	***LTE***	***Learn***	***VH***	***Bal***	***Wi-Fi***	***Rand***	
Urban Low Load	2710.4	2476.3	2468.9	2643	2305.9	677	2141.3	538.5
Urban Medium Load	3939.1	2784.8	3102.0	2593.6	2842	854.5	2596.9	807.7
Urban High Load	4611.4	2883.3	3483.1	3329.8	2946.5	1001.3	2152.3	1044.1
VANET Low Load	1992.4	1142.1	1707.6	1915.1	1665.6	1222.4	1670.5	748.22
VANET Medium Load	4197	1236.5	2274	2514.3	2120	1962.2	2172.6	1353
VANET High Load	5338.1	1250.2	2234.3	1789.8	2408.1	2206.9	2465.4	1535.2

6.4 Summary

This chapter introduced a novel semantic reasoning system for heterogeneous wireless networks to create a middleware that facilitates the process of managing and optimising various network architectures. The semantic reasoning system consists of two new semantic-based systems. The first one is a semantic knowledge base in which ontologies and a semantic rule base are employed to specify the QoS parameters and different network characteristics. The second system is a semantic inference engine that utilises fuzzy logic to create instances of the heterogeneous network ontology in a knowledge base and develop a fuzzy reasoner to utilise the knowledge base and the semantic rule base to infer the best action to optimise the network performance. The simulation results showed that the heterogeneous network outperformed the benchmark networks using two scenarios: the first utilised LTE and WMN, and the second included VANET. The proposed cognitive network enhanced network throughput by as much as 70% even when the LTE network utilised high bandwidth. The proposed semantic reasoning system could be used to represent parameters from upper layers in the networking protocol stack and provide a smart platform to integrate applications in smart homes or smart cities with the infrastructure for next-generation wireless networks.

Chapter 7

Conclusions and Future Work

This chapter concludes the thesis. Section 7.1 highlights the main contributions of the research work. Section 7.2 provides a conclusion to the work that has been described in this thesis;. Section 7.3 discusses the limitations and makes recommendations for future research.

7.1 Contributions

The main contributions of this thesis are as follows:

- A cognitive network framework obtains cross-layer information from each transmission device installed on the wireless node. This model is designed to create a self-optimised, self-configured and self-managed heterogeneous wireless mesh network to assist network operators in utilising non-overlapping frequency bands and to enhance network performance. It abstracts the network control system from the infrastructure, which simplifies the process of managing and optimising networks. The system receives information from multiple layers of the network protocol stack and develops a reasoning system to improve network performance and establish a self-organised network.

- A new rate adaptation algorithm based on reinforcement learning (RARE) is proposed to minimise the impact of the interference on the WMN. The algorithm optimises the transmission rate for the dynamic environment of WMNs. It considers the condition of the communication links on the neighbouring link to mitigate the negative impact of updating the transmission rate unnecessarily when the transmission failure is caused by channel error rather than interference. The results showed that the new algorithm achieve throughput that was as much as 90% higher than other state of the art rate adaptation algorithms.
- A new routing metric employs the transmission rate of the RARE algorithm to estimate the transmission link quality of WMNs. The proposed rate adaptation algorithm sets the transmission rate based on the link quality of the neighbouring nodes and the load on the Wi-Fi device. Thus, the transmission rate estimates the amount of interference and collision with other nodes and the load on the node. Thus, the best link quality provides the highest transmission rate.
- A novel heterogeneous wireless mesh network architecture overcomes the drawbacks of each transmission technology utilised in the network. The use of WMN increases the network capacity by utilising unlicensed frequency bands, which reduces the cost of buying additional LTE licensed frequencies. The LTE network is utilised to avoid low quality Wi-Fi links or connect island nodes when link failure occurs.
- A new routing algorithm is developed for the heterogeneous wireless mesh network architecture, which prescribes how the heterogeneous devices communicate with each other. The purpose of the proposed protocol is to create

the required routing tables in order to allow the heterogeneous wireless devices to send packets between LTE and WMN. The routing protocol specifies the set of routing tables that each node needs to maintain and the set of control messages that the heterogeneous nodes exchange among each other. It also specifies the type of transmission technology to be used to transmit these control messages.

- A new routing selection algorithm based on reinforcement learning named cognitive heterogeneous routing (CHR) is developed. CHR defines the steps required to select the transmission device at nodes that have both LTE and Wi-Fi devices. Reinforcement learning is employed to understand the previous actions and optimise the network performance. The simulation results showed that the proposed network and routing algorithm increased network performance by up to 200% compared with Wi-Fi-only networks and LTE-only networks.
- A new semantic knowledge-based system uses an extensible mark-up language (XML), which is a platform-independent technology that enables the ontology system to be processed and installed on any operating system. The ontology system simplifies the process of capturing the parameters of the heterogeneous systems from different layers of the network protocol stack and creates a high-level description of the heterogeneous wireless mesh network.
- A new semantic reasoning system controls different network architectures and selects RAN by employing ontology relationships between the cross-layer parameters of each network device. It abstracted the control of heterogeneous networks from the infrastructure. The use of semantic technologies and different reasoning systemssss enables the heterogeneous wireless network to operate and coordinate the different network architectures automatically and minimise the

need for human interaction. The use of the semantic reasoning system with heterogeneous network optimised the performance by up to 70% of the network throughput.

7.2 Conclusions

The main aim of this study was to develop a heterogeneous WMN by developing a smart framework to create middleware to facilitate the process of optimisation, configuration and management this network automatically. In this thesis, this main aim and the individual research objectives have been achieved.

The first objective of this research was to develop a cognitive network framework for heterogeneous WMN that works as an adaptor between various transmission technologies. The framework was designed to facilitate the integration among different wireless and wired transmission technologies by creating a relationship between technology-dependent parameters and storing the parameters in an ontology knowledge base. The proposed framework uses multiple network architectures and optimises their performances as a single virtual network.

For mitigating the negative impact of interference on a WMN, a new rate adaptation algorithm based on reinforcement learning (RARE) was developed to overcome the limitation of recent rate adaptation algorithms that were developed for infrastructure-based wireless networks. The transmission rate was used in this study as a metric to estimate the WMN channel quality; the node with a higher transmission rate had the better link quality. The algorithm learned from previous updates to avoid unnecessary changes in the transmission rate (e.g., due to channel error rather than interference), which caused packet loss. The proposed algorithm considered the transmission rate of the other nodes that compete to access the transmission channel, as well as the traffic load.

The next objective was to develop a new network architecture that utilised the non-overlapped frequency bands of different network types. For this purpose, a novel heterogeneous network architecture was proposed that combined LTE and WMN architectures to work as part of a single network. The LTE network was used to avoid congested Wi-Fi nodes and high interference paths in the WMN, while the WMN offloaded the load of the LTE network, which reduced the cost of using more license frequency bands and forwarded the data to another node when the LTE throughput was degrading.

To route the traffic between the different network architectures, a new heterogeneous WMN routing protocol was developed. The proposed routing protocol introduced a set of control messages. These control messages are exchanged using the available technologies on the nodes; for example, the LTE network could be used to send an IP address of the Wi-Fi network and the LTE network to the Internet Gateway in the proposed architecture. The heterogeneous routing protocol created and maintained routing tables on the heterogeneous nodes to forward data packets from the different networks just as if they were coming from the same network.

The next objective of this research was to develop decision-making algorithms to estimate the cost of transmitting the traffic through each network. A novel cognitive heterogeneous routing (CHR) algorithm was proposed to dynamically select the transmission technology in order to increase the overall network capacity and enhance the average throughput. The proposed algorithm considered the traffic load on the LTE network as a metric to estimate the cost of transmission over LTE and used the transmission rate as a metric for the Wi-Fi mesh network.

Finally, the last objective was to develop a mechanism to automatically configure different communication systems and to forward traffic demands through suitable transmission devices without the need to customise the software of the transmission devices or update the other layers of the Internet protocol stack. A novel semantic decision system was proposed, which used semantic reasoning with cross-layer parameters from the heterogeneous network architectures to manage and optimise the performance of the networks. This system obtained the required parameters from the routing protocol and employed these data to create relationships among technology-dependent parameters, which were then stored in an ontology knowledge base. This work introduced the use of ontologies and inference engines in managing, controlling and adding more network types to the heterogeneous WMN. The ontologies provided an abstract representation of heterogeneous networks, while fuzzy logic was used to represent the degree of QoS parameters in the ontology knowledge base. The semantic reasoning system utilised parameters from cross layers on each transmission technology to dynamically choose the RAN and avoid bad channel quality or a congested network. The reasoner in this study used the load and the channel quality indication (CQI) on the LTE network as metrics to estimate the cost of transmission over a LTE network, and used the transmission rate and success rate as metrics for the Wi-Fi mesh network, and LCD in addition to transmission rate for VANET network.

7.3 Limitations and Future Work

The scope of this work involved heterogeneous WMN with a cross-layer design. Although benefits have been demonstrated using data from the lower layers, the cognitive network framework can easily be extended to represent parameters from the upper layers in the networking protocol stack. This is particularly relevant in view of the latest trends in the Internet of things (IoT), Industry 4.0 and big data. It could also be used to provide a smart platform to integrate applications from smart homes or smart cities using the heterogeneous network to create an infrastructure for the next-generation wireless networks.

In future work, the security of the heterogeneous network architecture should be considered by including security protocols in the cognitive network framework. A reconfigurable and self-adaptive security mechanism is required to insure clients' privacy and service integrity.

The proposed framework could also be used to develop different services using an inference engine by adding new rules for reasoning using the knowledge base. The proposed model provides the foundation for the future exploration of the use of semantic technologies in wireless transmission technologies, such as wireless personal area network (802.14.5/ZigBee and Bluetooth), to support nodes with limited resources and to develop smart and self-configured network applications for the next-generation networks.

A potential research direction is the software defined network (SDN). SDN allows administrators to manage network services separately from the network infrastructure and enables the network to be programmable. The use of the proposed semantic reasoning system to abstract the infrastructure from the control system provides the foundation for further research on integrating it with an SDN. It is possible to allow network administrators to extend networks services by using customised ontology classes and to integrate ontology classes with SDN architecture.

Another potential research path is the use of high frequency bands, 3–300 GHz, in the heterogeneous network architectures. This part of the spectrum is not widely utilised, which means that it offers very high data rates, but does not suffer from high interference. However, these bands do suffer from a higher propagation loss; they also have a poor ability to penetrate objects, and any moisture in the air from rain and fog can significantly reduce the range due to the high attenuation in the signal. Heterogeneous WMN could utilise these bands to transmit at a very high data rate by adding new rules to the semantic reasoning system.

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