A Dissertation submitted in fulfilment of the requirements for the Degree of Doctor of Philosophy

Optimized Communication in 5G-Driven Vehicular Ad-hoc Networks (VANETs)

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Declaration Of Authorship

I, Ammara Anjum Khan, declare that this thesis titled, *Optimized Communication in 5G-Driven Vehicular Ad-hoc Networks (VANETs)*, is submitted in fulfilment of the requirements for the award of doctor of philosophy, in the Faculty of Engineering and Information Technology (FEIT), at the University of Technology Sydney.

I confirm that:

- This thesis is wholly my own work unless otherwise referenced or acknowledged
- The work is done solely while in candidature for a research degree at this University.
- All information sources and literature used are indicated in the thesis.
- This document has not been submitted/published for qualifications at any other academic institution.
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Date: October 14, 2019

Dedication

I would like to dedicate this work to my beloved mother (Najma Khan) and my late beloved father (Salah Uddin Khan) whose dreams for me have resulted in this achievement. I thank my mother with all my heart for all her prayers and unconditional love and care that kept me flourishing throughout the journey of my PhD.

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List of Abbreviations

VANETs	Vehicular Ad-hoc Networks
VCNs	Vehicular Communication Networks
VCI	Vehicular Communication Infrastructure
HetVANETs	Heterogeneous Vehicular Ad-hoc Networks
5G	Fifth generation
IoT	Internet of-Things
SD-IoV	Software Defined Internet of Vehicles
ITS	Intelligent Transportation Systems
V2V	Vehicle to Vehicle
V2I	Vehicle to Infrastructure
RSU	Road Side Units
CPRI	Common Public Radio Interface
D2D	Device-to-Device
E2E	End-to-End
QoS	Quality-of-Service
LTE-A	Long Term Evolution Advanced
EGT	Evolutionary Game Theory
SDN	Software Defined Networking
NFV	Network Function Virtualization
C-RAN	Cloud-Radio Access Network
MEC	Mobile Edge Computing
BBU	Base Band Unit
RRH	Remote Radio Head
OTN	Optical Transmission Network

List Of Abbreviations

FC	Fog Computing
FC-ZCs	Fog Computing-Zone Controllers
FC-CHs	Fog Computing-Cluster-heads
FC-Vehicles	Fog Computing-Vehicles
FC-BBUCs	Fog Computing BBU Controllers
ZC	Zone Controller
D	Delay
T	Throughput
C	Cost
CN	Core Network
eNB	Evolved node B
GA	Genetic Algorithm
Min-BBUC	Minimise number of FC-BBUCs
Cap-LB	Capacity Load Balance
Min-Delay	Minimize Delay
FC-ZC-per-BBUC-Bal	FC-ZCs per BBUC Balance Algorithm
CTL	Constant Traffic Load
H-FLGA	Hybrid-Fuzzy Logic guided Genetic Algorithm
FIS	Fuzzy Inference System
ToS	Type of Service
EC	Edge Cloud
CN	Core Network Cloud
KPIs	key performance Indicators

List of Parameters

$G = \langle N, H, S, u_{C_h} \rangle$	EGT game
$S = \{C_h, M\}$	Strategy set for vehicular nodes
s_i	Current strategy of node i
$N = \{1, 2, ..., n\}$	Set of vehicular nodes
$H = \{1, 2, ..., j\}$ with $j \subset N$	Set of clusters
u_{C_h}	net utility of a cluster head
$p_i(s_i)$	Cost function
T_{TC}	Total throughput of cluster
c_1	link capacity between the cluster head and the RSU
$c_j, j \subset N$	link capacity between a member j within the cluster and CH
d_H	distance between the cluster head and the RSU
$d_{M,j}$	distance between a member j from the cluster head
γ	Speed to convergence
$\bar{U}(t)$	average payoff of the entire population of clusters
$u_{C_{h_i}}(t)$	payoff to become a cluster head
$p_{H_i}(t)$	proportion of vehicles choosing cluster H_i
T_{TC}	average total throughput capacity of a given cluster
n_e	Equilibrium point
$ZC = \{ZC_1, ZC_2, ..., ZC_n\}$	set of Fog Computing Zone Controllers
n_{ZC}	Number of FC-ZCs
n_{BBUc}	Number of BBUCs
$Links = \{BBUC_i, ZC_j\}$	set of possible link pairs between FC-BBUCs and FC-ZCs
$Cost_{i,j}$	link cost for linking ZCs j and $BBUC_i$
D	average load demand across all BBUCs
D_i i^{th}	element indicating the total load demand in BBUCi
N_i	i^{th} total number of FC-ZCs connected to $BBUC_i$
$(ToS) = \{D, T, C\}$	requirement of customers based Throughout, Delay and Cost

List Of Parameters

ω_1	Weight of Min-BBUC cost function
ω_2	Weight of Cap-LB cost function
ω_3	Weight of Min-Delay cost function
ω_4	Weight of FC-ZC-per-BBUC-Bal cost function
ω_5	Weight of CTL cost function
$d_{fronthaul}$	maximum front-haul distance
$\upsilon_{fronthaul}$	link propagation speed
δ_{RTT}	Round Trip Time
$\tau_{OWD}(ms)$	one way delay

Abstract

Next generation Vehicular Ad-hoc Networks will be dominated by heterogeneous data and additional massive diffusion of Internet of Things (IoT) traffic. To meet these objectives, a radical rethink of current VANET architecture is essentially required by turning it into a more flexible and programmable fabric.

This research endeavours to provide next generation 5G-driven VANET architecture, with solutions for efficient and optimized communication.

This thesis first introduces an innovative 5G-driven VANET architecture to provide flexible network management, control and high resource utilization, leveraging the concepts of SDN, C-RAN and Fog Computing. A new Fog Computing (FC) framework (comprising of zones and clusters) is proposed at the edge of the network to support vehicles and end users with prompt responses, and to avoid frequent handovers between vehicles and RSUs. The key results are improved throughput, reduced transmission delay and minimized control overhead on the controller.

Furthermore, a novel Evolutionary Game Theoretic (EGT) framework is presented to achieve stable and optimized clustering in the Fog Computing Framework. The solution of the game is presented to be an evolutionary equilibrium. The equilibrium point is also proven analytically and the existence of an evolutionary equilibrium is also verified using the Lyapunov function. The results are analysed for different number of clusters for different populations and speeds. An optimal cost is suggested that defines an optimum clustering thus reducing an overhead of frequent cluster reformation.

In addition, this thesis provides a Hybrid-Fuzzy Logic guided Genetic Algorithm (H-FLGA) approach for the SDN controller, to support diversified quality of service (QoS) demands and dynamic resource requirements of mobile users in 5G-driven VANET architecture. The proposed Fuzzy Inference System (FIS) is used to optimize weights of multi-objectives, depending on the Type of Service (ToS) requirements of customers. The results proved that the proposed hybrid H-FLGA performs better than GA. The results improve spectral efficiency and optimizes connections while minimizing E2E delay and further facilitates the service providers to implement a more flexible customer-centric network infrastructure.

Furthermore, an end-to-end (E2E) network slicing framework is proposed to support customized services by managing the cooperation of both the RAN and Core Network (CN), using SDN, NFV and Edge Computing technologies. A dynamic radio resource slice optimization scheme is proposed to slice the overall bandwidth resources for mission critical and non-mission critical demands. The results meet ultra reliability and E2E latency of mission-critical services.

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Chapter 1

Introduction

Next generation Vehicular Ad-hoc Networks (VANETs) will be dominated by heterogeneous data traffic and additional massive diffusion of Internet of Things (IoT) traffic. To support the exponential growth of heterogeneous data traffic and

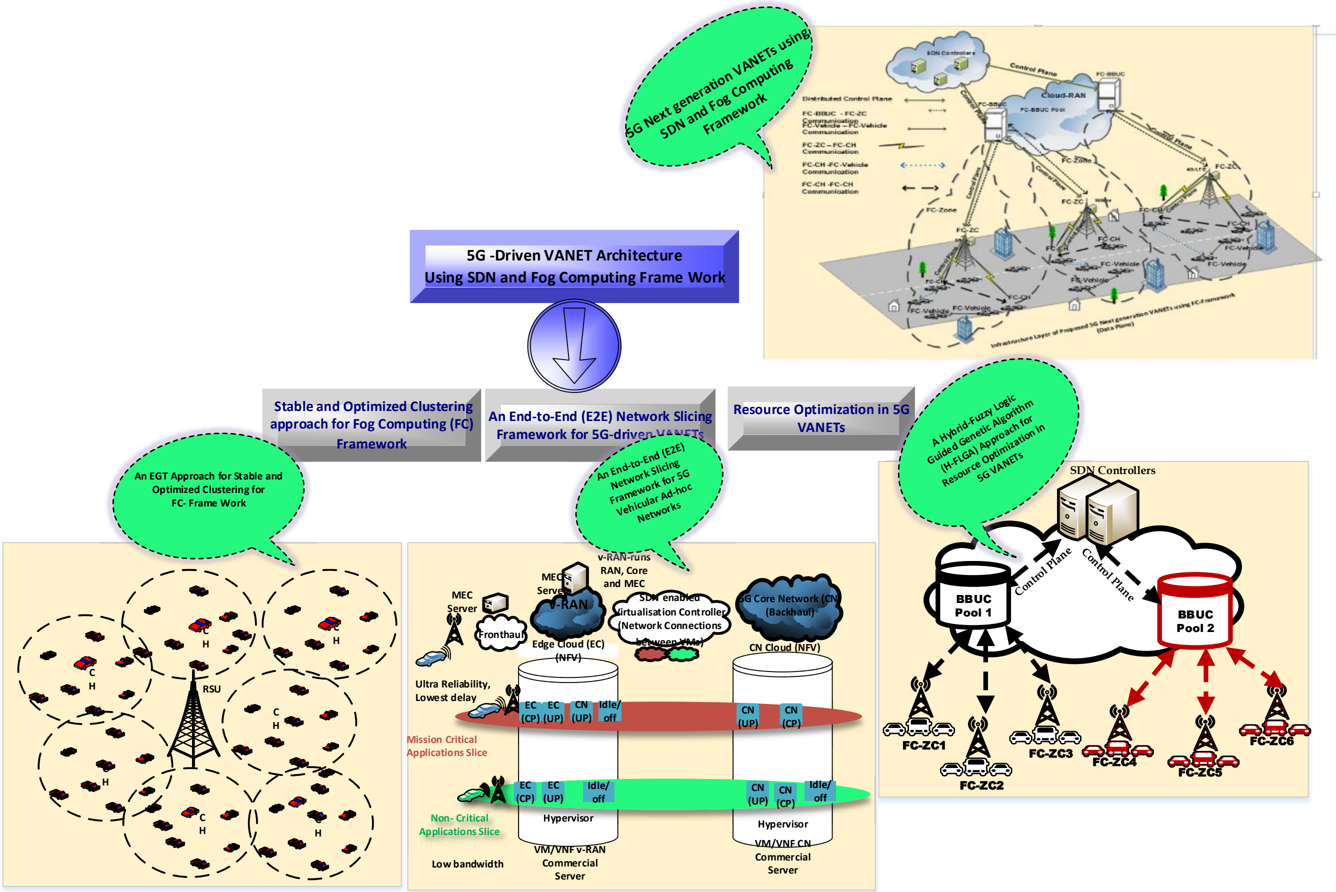

Figure 1.1: Optimized Communication in VANETs

diversified quality of service (QoS) demands, network resources need more flexible and optimized resource allocation strategies. In recent years, VANETs have rapidly evolved and gained significant attention from both research and industry, as they can provide a platform to connect a massive number of sensors for Internet of Things (IoT) applications through wireless communication infrastructures. Integrating different wireless access networks such as cellular (3G, 4G, 5G, LTE, LTE D2D, 3GPP) and IEEE 802.11p/DSRC, the Heterogeneous VANETs (HetVANETs) are expected to be a good platform to meet diversified communication requirements of next generation VANETs. Besides these challenges, another major challenge is an ever increasing network size, density and highly evolved physical layer technology, which becomes an underlying bottleneck hindering the performance of HetVANETs. This is due to the highly dynamic mobility, heterogeneity and handoffs between different wireless infrastructures and the inflexibility of protocol deployment. Therefore, conventional heterogeneous Vehicular Ad-hoc Network architectures lack in flexibility on the large scale and cannot efficiently deal with the increasing demands over different access networks. Nowadays, Software Defined Networking (SDN), an enabler of 5G technology, is leading towards a revolutionary paradigm to facilitate flexible network management and optimization on the large scale with unified abstraction [10], [11]. Besides SDN, Cloud Radio Access Network (C-RAN) has also been widely accepted to be a promising solution for heterogeneous networks [10]. In addition, Cloud Radio Access Network (C-RAN) is expected to be a potential candidate of next generation radio access networks that can facilitate rapid and inexpensive network deployments by exploiting the extensive computation resources offered by cloud platforms [12], [13], [2], [14]. Moreover, the idea of Network Function Virtualization (NFV) is also proposed to solve many problems caused by the proprietary nature of existing hardware appliances. NFV decouples the software implementation of network functions from the underlying hardware and has the potential to lead to significant reductions in operating expenses (OpEx) and capital expenses (CapEx).

In order to meet the before mentioned challenges, a radical rethink of current VANET architecture is essentially required. According to our vision, this evolution can be achieved by turning it into a more flexible and programmable fabric, by integrating 5G enabled technologies such as Cloud-RAN, SDN and NFV. Besides

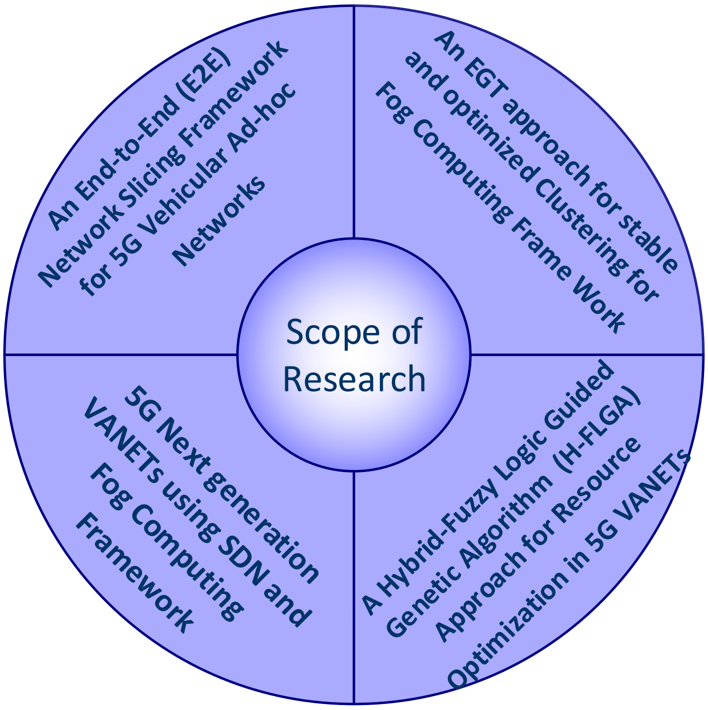

Figure 1.2: Scope of Thesis

these technologies, Edge Computing and Fog Computing technologies are also aimed at offering ultra low latency, high resource utilization, and real-time access to radio access that can be used by differentiated services and QoS optimization platforms. These 5G-driven technologies can jointly be used to provide a multitude of diverse services and are expected to substantially improve resource sharing over a common underlying physical infrastructure. Other than these challenges, accommodating high volumes of traffic with a diverse set of performance and service requirements is also a major challenge. Reserving radio resources for a particular application may lead to over-provisioning of resources [15]. There is a need for efficient on-demand and instant resource allocation strategies [16]. With the evolution of 5G-driven technology, network slicing has also emerged as a major new networking paradigm, which is considered to achieve high utilization of both communication and computing resources and minimize the infrastructure deployment cost for operators [17], [18].

The proposed 5G-driven research in VANETs will emerge in an attempt to address the following challenges;

- Improved throughput
- Minimized overhead on Controller
- Minimized transmission delay
- Stable Cluster sizes
- Optimum Clustering
- QoS Provisioning
- Minimized E2E latency
- Capacity enhancement
- Optimized Front-haul connections
- Optimum resource allocation
- Implementation of Customer centric infrastructure depending on dynamic customer needs.
- Ultra reliability
- Reductions in operating expenses (OpEx) and capital expenses (CapEx)

1.1 Thesis Statement

Vehicular Ad-hoc Networks (VANETs) have been promoted as a key technology towards the evolution of upcoming 5G networks. Next generation 5G-driven VANETs, dominated by heterogeneous data, bring new challenges like diversified QoS demands including efficient resource management and resource optimization. To meet these objectives, a radical rethink of current VANET architecture is essentially required by turning it into a more flexible and programmable fabric. This can be achieved through technological improvements facilitated by emerging technologies like Software Defined Networking (SDN), Network Function Virtualization (NFV), Cloud-RAN (C-RAN) and Fog/Edge Computing. These technologies can jointly be used to provide a multitude of diverse services and resource sharing using a globalized view over a common physical VANET infrastructure. Researchers have provided multiple solutions for optimized communication in VANETs, but no work has been yet proposed that suggest efficient resource allocation and optimized communication with the 5G perspective.

1.2 Objectives and Overview of Thesis

The main objective of this thesis is to provide efficient solutions for optimized communication in 5G driven VANETs, to support the exponential growth of heterogeneous data traffic and to meet diversified quality of service (QoS) demands and dynamic resource requirements of users.
An innovative 5G-driven VANET architecture is proposed, leveraging the concepts of SDN, C-RAN and Fog Computing technologies. A novel lightweight and semi-distributed approach, entitled the Evolutionary Game Theoretic (EGT) approach, is proposed to achieve stable and optimized clustering in VANETs. To achieve optimization of resources in 5G-driven VANETs, a Hybrid-Fuzzy Logic guided Genetic Algorithm (H-FLGA) approach is proposed for the SDN controller, to solve a multi-objective resource optimization problem. Five different objectives of network resource provisioning are formulated and the problem is solved using the Fuzzy Logic Guided Genetic Algorithm. The Fuzzy Inference system (FIS) is introduced to optimise weights of multi-objectives, depending on the Type of Service (ToS) requirements of customers. The H-FLGA scheme improves spectral efficiency and optimizes connections while minimizing E2E delay and further allows the service providers to implement a more flexible customer-centric network infrastructure. To support customized services in 5G-driven VANETs, the proposed E2E network slicing framework manages the cooperation of both the RAN and Core Network (CN), using SDN, NFV and Edge Computing technologies. A dynamic radio resource slice optimization scheme slices the overall bandwidth resources for mission critical and

non-mission critical demands, by keeping in view resource elasticity requirements. The proposed slicing solution meets ultra reliability and E2E latency of mission-critical services.

1.3 Thesis Outline and Contributions

This section provides an outline of the thesis and summarizes the main contributions.

- In Chapter 2, an extensive review of relevant literature is presented - in particular, features and challenges of Vehicular Ad-hoc Networks (VANETs) comprising of heterogeneous infrastructures such as, cellular (3G, 4G, LTE, 5G, LTE D2D, 3GPP) and IEEE 802.11p/DSRC. Further to this, some challenges of current Vehicular Communication Networks (VCNs) including Heterogeneous Vehicular Ad-hoc Networks (HetVANETs) are explained in detail. An overview of 5G-driven technologies such as Software Defined Networking (SDN), Cloud-Radio Access Network (C-RAN), Network Function Virtualization (NFV) along with their implementation in VANETs is also discussed.

- In Chapter 3, an innovative next generation 5G VANET architecture is proposed by employing the concepts of SDN, C-RAN and fog computing technologies. In particular, a description of the high level design of proposed architecture along with the description of architecture components and their roles contributed in the architecture are discussed. Moreover, a new Fog Computing (FC) framework is proposed at the edge of the network, to support vehicles and end users with prompt responses. Furthermore, some benefits of the proposed architecture associating its feasibility in HetVANETs, are also discussed. Using SDN and C-RAN technologies, the proposed architecture provides flexibility, programmability and effective resource allocation, thus leading towards significant reductions in OpEx. The performance of the proposed architecture is investigated by comparing the transmission delay, throughput and control overhead on the controller with other architectures. Simulation results show improved throughput, reduced transmission delay and minimized control overhead on controllers.

- In Chapter 4, we look into the problem of cluster instability in VANETs for the proposed FC framework in chapter 3. We propose a novel Evolutionary Game Theoretic (EGT) approach to model the interactive decision making process between vehicular nodes, in order to automate the clustering of nodes and nomination of cluster heads, to achieve stable and optimized clustering in VANETs. The equilibrium point is proven analytically and the existence of evolutionary equilibrium is also verified using the Lyapunov function. Two performance evaluation approaches are used to investigate the behaviour and performance of the proposed game, under different populations, speeds and cost functions. Our first approach is based on *static scenarios* and in our second approach, we use the *Manhattan grid* as a mobility model to investigate the behaviour of our proposed game. Simulation results show that the proposed framework is able to maintain cluster stability, as the clusters evolve towards balanced sizes and the system converges with an average total throughput of clusters. Furthermore, the results reveal that the proposed approach is lightweight, semi-distributed and allows faster convergence, thus reducing the signalling overhead and complexity in large scale VANETs.

- In Chapter 5, further extending the work of our proposed 5G-driven VANET architecture, a Hybrid-Fuzzy Logic guided Genetic Algorithm (H-FLGA) approach is proposed for the SDN controller, to solve a multi-objective resource optimization problem. The proposed approach formulates five different objectives of network resource provisioning, particularly focussing on network aspects such as capacity, delay, number of FC-BBUCs and the traffic load. The Fuzzy Inference system (FIS) is proposed to optimise weights of multi-objectives, depending on the Type of Service (ToS) requirements of customers. Different options are weighted using the proposed FIS and multi-objective weights are optimized, to provide an optimal solution. The results of the proposed H-FLGA approach are compared with GA and our propsed 5G driven VANET architecture in [9]. The proposed approach shows the minimized value of multi-objective cost function when compared with GA. Results show that the proposed H-FLGA approach minimizes E2E delay in comparison with GA and 5G driven VANET architecture. The proposed scheme will provide the network service providers with an opportunity to implement a more flexible customer-centric network infrastructure, by improving spectral efficiency. Moreover, the proposed approach can also be used to support energy efficient optimization, as some idle BBUC's may be switched off without any adverse effect on the overall system, thus reducing OpEx.

- In Chapter 6, an end-to-end E2E network slicing framework is proposed to achieve the desired level of QoS provisioning for customized services in 5G-driven VANETs. The proposed scheme considers managing the cooperation of both RAN and Core Network (CN), using SDN, NFV and Edge Computing technologies. The proposed framework distributes some services of 5G core close to cell sites using Mobile Edge Computing (MEC) technology and keep other services with centralized processing, to meet desired levels of KPIs. The distribution of both mission critical and non-critical demands is achieved through SDN-enabled NFV technology. Furthermore, a dynamic radio resource slice optimization scheme is proposed, handling a mixture of both best-effort traffic and mission-critical traffic. The problem is solved using the Genetic Algorithm (GA). The overall bandwidth resources are sliced for mission critical and non-mission critical demands, by keeping in view resource elasticity requirements. The results are compared with the previously proposed VANET architecture. Simulation results show the effectiveness of the proposed network slicing framework for the 5G network.

- In Chapter 7, the key contributions and results of the thesis are summarised. Some possible future research directions are also discussed.

1.4 Related Publications

The publications relating to the work of the thesis are as follows;

- A new hierarchical 5G next generation VANET architecture is proposed by employing the concepts of SDN, C-RAN and fog computing technologies, to effectively allocate resources in VANETs with a global view. The transmission delay, throughput and control overhead on the controller are analyzed and compared with other architectures. Simulation results indicate improved throughput, reduced transmission delay and minimized control overhead on controllers. (Chapter 3). Ammara Anjum Khan, Mehran Abolhasan, and Wei Ni. 5G next generation VANETs using SDN and fog computing framework. *In Consumer Communications & Networking Conference (CCNC). 2018 15th IEEE Annual, pages* 1-6. IEEE, 2018 [9].

- An Evolutionary Game Theoretic (EGT) approach is presented to solve the problem of cluster in-stability in VANETs. The proposed approach automates the clustering of nodes and nomination of cluster heads and achieve optimum clustering by using the cost function. The equilibrium point is proved analytically and the stability of equilibrium point is tested using the Lyapunov function. (Chapter 4). Ammara Anjum Khan, Merhan Abolhasan, and Wei Ni. An Evolutionary Game Theoretic Approach for Stable and Optimized Clustering in VANETs. *IEEE Transactions on Vehicular Technology*, 67(5):4501-4513, 2018. [19]

- A Hybrid-Fuzzy Logic guided Genetic Algorithm (H-FLGA) approach is proposed for the SDN controller, to solve a multi-objective resource optimization problem for 5G driven VANETs. The results of the proposed hybrid H-FLGA approach are compared with GA and 5G driven VANET architecture in [9]. The proposed hybrid H-FLGA approach shows the minimized value of multi-objective cost function when compared with GA. (Chapter 5). Khan, A., Abolhasan, M., Ni, W., Lipman, J., & Jamalipour, A. (2019). A Hybrid-Fuzzy Logic Guided Genetic Algorithm (H-FLGA) Approach for Resource Optimization in 5G VANETs. *IEEE Transactions on Vehicular Technology.*

- An E2E network slicing framework is proposed to achieve QoS provisioning among customized services in 5G-driven VANETs, by considering both RAN and Core Network (CN) using SDN, NFV and Edge Computing technologies. Furthermore, a dynamic radio resource slice optimization scheme is formulated mathematically. Simulation results reveal that the proposed slicing framework is able to optimize resources and deliver the targeted KPIs of mission critical demands.(Chapter 6). Ammara Anjum Khan, Merhan Abolhasan, Justin Lipman, Wei Ni and Abbas Jamalipour. An End-to-End (E2E) Network Slicing Framework for 5G Vehicular Ad-hoc Networks (Under review in IEEE Journal on Selected Areas in Communications - Special Issue on Network Softwarization & Enablers.)

Chapter 2

Literature Review

2.1 Introduction

This thesis explores different solutions to provide optimized communication in 5-driven Vehicular Ad-hoc Networks. This chapter includes general discussions of Vehicular ad-hoc Networks including heterogeneous VANETs and their challenges. Moreover, motivations behind using 5G-driven technologies are also discussed. The key topics of this chapter includes:

- Vehicular Ad-hoc Networks, including their features, applications, and components of Vehicular Communication (VC);
- Vehicular Communication Infrastructure (VCI);
- Heterogeneous Vehicular Ad-hoc Networks (HetVANETs);
- Vehicular communication Infrastructure (VCI) and HetVANETs based on their advantages and disadvantages;
- Limitations of HetVANETs and description of Software Defined Internet of Vehicles (SD-IoV) VANET architecture.
- Detailed description 5G-Driven technologies including;
  - Software Defined Networking (SDN) and its applications in Vehicular Ad-hoc Networks.
  - Cloud Radio Access Network Architecture (C-RAN)

– Network function Virtualization (NFV)

2.2 Vehicular Ad-hoc Networks (VANETs)

With recent advances in Intelligent Transportation Systems (ITS), Vehicular Ad-hoc Networks (VANETs) have attracted a large interest in both academia and industry. VANETs can be considered as a potential core of ITS that is envisioned to offer a wide variety of versatile services ranging from transportation and road safety to infotainment applications like web browsing, video streaming, file downloading [20]. Smart vehicles are expected to heavily influence daily life and to motivate a huge market in the near future. With the rapid development of wireless communication technologies, vehicles can utilize Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communications with the help of on-board devices to provide wireless communication services among vehicles and vehicle to road side infrastructure [21], [22].

The era of the fifth generation (5G) cellular networks is rapidly evolving. Fifth generation (5G) wireless communication networks emerge as a strong platform to support V2V and V2I connections efficiently and securely as well as the integration with V2X scenarios. The Internet of Vehicles (IoV) uses the wireless communication infrastructures to allow vehicles to be connected to new radio technologies, and can be supported by 5G networks. 5G networks are anticipated to support a number of vertical industries characterized by diversified applications including future IoV applications and Intelligent Transport Systems (ITS) in scenarios like high mobility, dynamic network topology, and high data volume with varying QoS demands [23]. With the increasing demands of new techniques in Vehicular Ad-hoc Networks, several new applications are emerging in the field of VANETs to integrate the capabilities of next generation wireless networks to vehicles [24]. However, these emerging applications require larger, more secure storage and complex computation capabilities, hence bringing new resource challenges to Vehicular Ad-hoc Networks (VANETs). To meet the increasing demands of radio and computing resources, Vehicular Ad-hoc Networks take the advantages of cloud computing and fifth generation technologies allowing them to evolve towards next generation VANETs. Next generation Vehicular Ad-hoc Networks are envisioned to carry computing and communication platforms, and will have enhanced sensing capabilities that will facilitate transportation safety and efficiency.

2.2.1 Applications of VANETs

The applications of VANETs can be classified as;

1. **Safety Warning Applications:** These applications aim to broadcast message alerts about dangerous events on the road with wireless communication technology and also warn drivers receiving such alerts. These applications have a strict delay requirements for safety and time critical messages dissemination. These applications mostly rely on Vehicle to Vehicle (V2V) communication. Examples include the emergency electronic brake light, the highway merge warning, lane changing assistance, traffic signal violation warning including accident avoidance such as cooperative collision avoidance, crash warning and roll-over warning.

2. **Entertainment Applications and General Information Services:** The main objective of these applications is to provide entertainment services to the passengers and to improve traffic efficiency. Examples include interactive communication services (such as internet access, music download, interactive games while travelling), including traffic information systems, weather information, optimum route selection, value added services and gas station or restaurant location [25], [21]. These applications usually rely on Vehicle to Infrastructure (V2I) communication.

2.2.2 Vehicular Communication (VC)

There are two main components of Vehicular Communication;

1. Road-Side Units (RSUs):

   RSUs are static components positioned at strategic positions across the roads and serve as central controllers to provide direct wireless communication services to the Vehicles. RSUs are sensors that are connected to the backbone networks to provide reliable communication. Furthermore, RSUs are equipped with network devices to support Dedicated Short Range Communication (DSRC) using IEEE 802.11p. Examples include GSM, WLANs and WiMAX [25].

2. On Board Units (OBUs'):
   Each vehicle is equipped with On Board Unit that act as a central processing unit (CPU). With the help of OBUs', vehicles can send and receive packets and perform routing functions. These OBUs' enable the vehicles to send and receive messages to other vehicles or RSUs within their range using a wireless communication medium. Nowadays most of the applications provided by Intelligent Transportation systems depend on the geographical locations of the sender and receiver, therefore, OBUs' are equipped with a Global Positioning System (GPS) or Differential Global Positioning System (DGPS) receivers.

2.2.3 Vehicular Communication Infrastructure VCI

Vehicular Ad-hoc Networks do not rely only on the fixed infrastructure to provide ubiquitous connectivity between vehicles [21], [24]. Vehicular Communication Infrastructure (VCI) is categorized as follows;

- ***Vehicle to Vehicle (V2V) Communication or Inter Vehicle Communication (IVC)***: V2V or IVC communication uses a multi-hop multicast or broadcast mechanism for message dissemination. This type of communication is adopted when a vehicle is not directly connected to the RSU. V2V requires less bandwidth for message dissemination as compared to V2I.

- ***Vehicle to Infrastructure (V2I) or Infrastructure to Vehicle (I2V) Communication or Roadside Vehicle Communication (RVC)*** : In V2I, I2V or RVC communication, the message is disseminated using the RSUs and the vehicles. The RSU sends or broadcasts a message to all the vehicles within its vicinity using a single hop transmission and uses multihop transmission to broadcast message to vehicles that are not coming directly under its vicinity. Sparse Roadside Vehicle Communication (SRVC) and Ubiquitous Roadside Vehicle Communication (URVC) are subcategories of V2V or I2V infrastructure. V2I communication requires higher bandwidth as compared to bandwidth demand for V2V Communication. For instance, to broadcast speed warnings or broadcasting speed limits, the RSU will determine the appropriate speed limit by checking internal database and will broadcast the speed limit warning message to vehicles periodically. Furthermore, the RSU will also require additional bandwidth to issue an audio or visual warning message to intimate the vehicle to reduce its speed, if a vehicle violates the desired speed limit rules [25], [26].

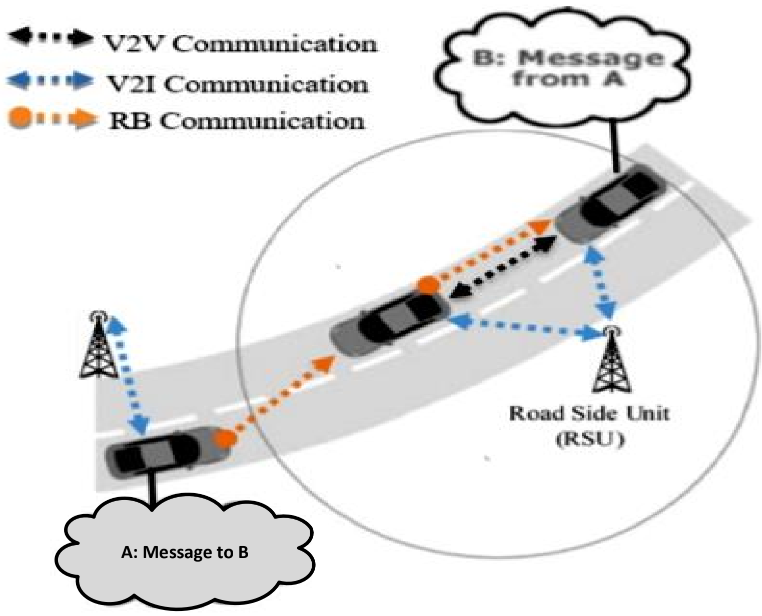

Figure 2.1: Vehicular Communication Infrastructure in the ITS systems [1]

- ***Hybrid Vehicle Communication (HVC)***: HVC uses both inter-vehicle (V2V) communication and road-side (V2I) or (I2V) communication. Nowadays there are variety of ITS cooperative applications that use HVC infrastructure. These services include traffic management, road accidents warning, interactive games, infotainment services including road condition sensing and many other applications [26]. Routing-based (RB) Communication is used in cases where the path is not directly provided and the packet will be routed using RB Communication as shown in Fig. 2.1.

2.2.4 Features of VANETs

VANETs have some other intrinsic features that distinguish them from other Ad hoc Networks [25], [24], [26]. The following are the characteristics of VANETs;

- ***Frequently changing topology and Frequently disconnected Network:*** In VANETs, the speed of vehicles is frequently changing and the topology is dependent on the mobility of vehicles. Moreover, due to the rapid changes in the topology, the connectivity between vehicles is hardly maintained. This frequent network disconnection problem should be considered while designing a VANET protocol.

- ***Delay Constraints:*** In some of the ITS applications, such as emergency brake warning, the dissemination of the message is very time critical to avoid a car crash. For these applications, it is more important to control delay constraints instead of providing high data rates.

- ***Predicting the Mobility of Vehicles***: In VANETs, the mobility of vehicles is constrained by the road directions and traffic patterns. In order to design a VANET protocol, these mobility models and predictions of the future directions of the vehicles is important to be considered.

- ***Urban and Highway Traffic Scenarios:*** Since VANETs operate in two different types of traffic scenarios such as *Highway* and *Urban*. The highway scenario is simple due to having no obstacles, whereas the urban traffic scenario is complex comprising of streets, buildings and obstacles. While designing a VANET protocol, both types of traffic scenarios should be considered, including the affects caused in communication due to shadowing and path loss in urban traffic environments.

- ***Rich in Resources:*** VANET nodes are equipped with OBUs and have enough resources like power, memory and processing capabilities. OBUs are usually mounted on-board a vehicle and are used for exchanging information with RSUs or with other OBUs. The OBUs are comprised of a Resource Command Processor (RCP) and resources contain a read/write memory that is used to store and retrieve information. OBUs also contain a user interface that connects to other OBUs and a network device for short range wireless communication based on IEEE 802.11p technology.

2.2.5 Heterogeneous Vehicular Ad-hoc Networks (HetVANETs)

Heterogeneous Vehicular Ad-hoc Networks integrate Direct Short Range Communication (DSRC) with other cellular networks like 3G, 4G, LTE, LTE with D2D, 3GPP and 5G networks. HetVANETs are a potential solution to meet wide variety of future ITS applications and services.

Challenges of Vehicular Communication Networks (VCNs)

In a typical VCN scenario, vehicles equipped with on-Board-Units (OBU's) communicate with adjacent peer vehicles using Vehicle-to-Vehicle (V2V) communication, and receive services from infrastructures (such as : Road Side Units (RSUs), Cellular Base Stations (BSs) and Wi-Fi Access Points (APs) using Vehicle-to-Infrastructure (V2I) communication. In recent years, Vehicular Communication Networks (VCNs) have gained significant attention from both research and industry as they play a fundamental role in enabling smart vehicles to get connected to surrounding vehicles and the internet through wireless communication infrastructures [27], [28]. For example, in case of a traffic accident, emergency information will be disseminated to all vehicles in that area via V2V communication and detour routes will be provided to the all other vehicles moving towards that site. Moreover, by exploiting the benefits of cloud computing, real time traffic data is collected from vehicles and deployed sensors across roadside infrastructure, and optimal decisions are made by the travel planner applications. However, to meet optimal decision making on a large scale and to facilitate flexible network control and optimization in VANETs, the concept of Internet of Vehicles (IoV) comes into play. This is the platform where all drivers and passengers can enjoy the services of ITS through internet. IoV is expected to gain a large share of future market based on its applications and tremendous market demands [3]. Moreover, there is an assumption that is further supported by a report from Gartner forecasting that there will be more than 250 million connected vehicles on road by 2020. Despite the efforts made in the field of VCN in recent years, there are still many challenges left unaddressed.

1. The current key research challenge of VANETs is to identify how to efficiently exploit the heterogeneous VCNs [29]. The heterogeneity of VCNs can be further discussed as;

    - **Wireless LANs (Wi-Fi and DSRC):** Wireless LANs (WLANS) including both WiFi and Direct Short Range Communication (DSRC) both have the potential to be easily utilized in this scenario. WLANs have their own advantage over other cellular technologies but there is a lack of consistency in providing services for VCN scenarios. For example, WLANs offer high data rates but at the same time their availability is dependent on local infrastructures with limited coverage.
    - **Dynamic Spectrum Access (DSA) technologies over TVWS (TV White Space):**Dynamic Spectrum Access (DSA) technologies over TVWS (TV White Space) can be utilized in VCN scenarios [30], [31]. TVWS spectrum has a great potential to deal with VCN scenarios but, unfortunately, consistency in services cannot be provided for VCN scenarios, since, the resources required for TVWS are opportunistic and location based [3].
    - **Cellular Technologies:** Compared to WLANs, cellular networks provide the widest communication coverage area and most reliable connections, while concurrently their capacity is limited with increasing traffic load in VCN scenarios. Future vehicular networking is expected to adopt current cellular solutions like 3G, 4G, LTE, 3GPP and is expected to be heterogeneous in terms of resources and network topology. 4G and LTE are proposed to support vehicular communication scenarios [32]. For example, a vehicle user can take benefits from wide coverage, low latency and high throughput of LTE cellular networks. However, due to high vehicle mobility and dynamic network topology, it is relatively challenging to provide satisfied ITS services only through LTE. Especially in VCN scenarios, where the number of vehicle users increases in the cell, the strict latency requirements of safety related ITS applications cannot be guaranteed by LTE networks alone. Heterogeneous Vehicular NETworks (HetVNET), integrating different access networks technologies like DSRC and

LTE, are expected to be a potential solution to meet various ITS service requirements [27]. A unified wireless access standard called the Continu-

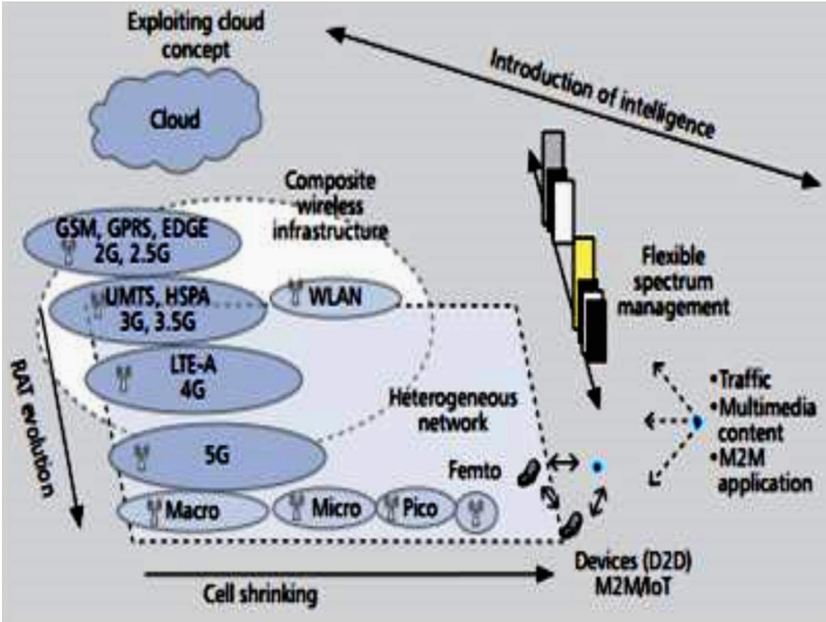

Figure 2.2: Evolution of mobile networks [2]

ous Air Interface for long and medium range (CALM M5) is also defined for vehicular communication [33]. This standard is a product of unification efforts made by the International Standards Organization-Technical committee (ISO-TC 204 WG16) to define a single uniform standard to support unified wireless access to improve VCN performance through increased capacity, flexibility and redundancy in packet transmission and reception. They combined several related air interface protocols and parameters on top of IEEE 802.11p architecture with support for existing cellular technologies. However, the current key research challenge of VCNs is the lack of the central communication co-coordinator associated with all the existing wireless access infrastructures related to vehicular communication set-up, implementation and deployment [3], [1].

- **Heterogeneity of V2I and V2V transmission modes:** On the hand, the heterogeneity related to both V2I and V2V transmission modes also poses difficult challenges with high resource utilization efficiency and enhanced capacity on the large scale. Since, V2I can provide internet access to vehicles and V2V can be used direct transmission same like Device-to-

Device (D2D) communication in LTE networks.

- **IEEE 802.11p based standards:** IEEE 802.11p technology is widely encouraged by vehicle manufacturing industries across the world. In the USA, it is promoted through VII and VSCC, Japan through Advanced Safety Vehicle project (ASV), Europe through C2C-CC and Germany through SeVeCOM [10]. Compared to cellular technologies, the estimated deployment cost of IEEE 802.11p (WAVE (Wireless Access in Vehicular Environments)) is predicted to be relatively low. This protocol is a work-in-progress by the IEEE working group. The medium access control (MAC) and physical (PHY) layers are based on the IEEE 802.11a standard. DSRC based on the IEEE 802.11p has gained popularity due to its easy deployment, low cost and capacity to support V2V communication [30]. However, it is dependent on ubiquitous deployment of road side infrastructures and suffers from scalability issues related to the limited radio range and unbounded delay [34]. Table. 2.1 also shows a comparison of different wireless communication technologies in vehicular networks with respect to bandwidth, allocated spectrum, support for mobility, bitrate, transmission power and communication range [1].

2. **Challenge to meet diverse QoS requirements in VCN:** In a VCN scenario, each service request has different QoS requirements. For example, safety related ITS services require low latency and high reliability requirements, some applications like delay tolerant applications are more bandwidth consuming, video streaming services have strict constraints on stable connection and high speed. Future connected vehicles are expected to support diverse QoS requirements for different ITS services with a global view of all service requests, so as to make optimum decisions for resource sharing for all ITS service requests.

3. **Lack of management and control of VCNs on the large scale:** With an ever increasing vehicular network size and density as well as highly evolved physical layer technology, the control and management of VCNs becomes highly challenging, impeding the performance of Heterogeneous VCNs. Due to the high mobility and rapidly changing topology of VCNs, the handoffs

among different wireless access infrastructures are more frequent as compared to traditional wireless networks, thus causing service interruptions. A large number of wireless network infrastructures and spectrum resources may be wasted and thereby lead to the low Quality of Experience (QoE) of vehicle users. Therefore, the access and admission control mechanism should be fairly coupled with the QoS driven resource allocations process. There is a need to develop some unified ways to deal with control and management issues rising in Heterogeneous VANETs on a large scale. To deploy new services and protocols, a large amount of underlying network devices need to be configured and modified by network operators [10].

Although mobile cellular technologies have a great potential of providing wide coverage to vehicle user to provide wide variety of ITS service requirements, strict requirements for real-time services cannot always be guaranteed by cellular networks [1]. This is due to changing traffic demands and mobility of vehicles in VCNs. Therefore, the Heterogeneous Vehicular Network (HetVNET), which integrates different cellular communication networks with DSRC, is a potential solution to meet communication requirements of different ITS applications and services without the need of pervasive roadside infrastructures [27]. All of the above mentioned issues related to current VCNs are considered as the building blocks of progress towards more efficient future architectures to support future ITS applications.

2.2.6 Challenges of Heterogeneous Vehicular Ad-hoc Networks (HetVANETs)

Building Heterogeneous Vehicular Networks, requires a deep understanding of heterogeneity and its associated challenges in VCNs. Therefore, Heterogeneous Vehicular Ad-hoc Networks (HetVNETs), which integrate DSRC with other cellular technologies, can meet different future ITS service requirements [27]. Recently the Qualcomm Snapdragon automotive development platform was released to support auto manufacturers and suppliers to test, deploy and transform vehicular applications. This platform supports not only LTE but also IEEE 802.11p for DSRC. In this section, we discuss some major advantages and challenges that are related to

Table 2.1: Comparison of high speed Wireless Communication Technologies for Vehicular Networks [1]

Wireless Features	**Wi-Fi**	**802.11p(WAVE)**	**Infrared**	**Cellular**
Standards	IEEE	IEEE, ISO, ETSI	ISO	ETSI, 3GPP
Channel Bandwidth	1-40MHz	10MHz, 20MHz	N/A(Optical carrier)	25MHz(GSM), 60MHz(UMTS)
Allocated Spectrum	50MHz at 2.5GHz 300MHz at 5GHz	30MHz (EU) 75MHz (US)	N/A(Optical carrier)	(Operator-dependent)
Frequency Band(s)	2.4GHz, 5.2GHz	5.86GHz-5.92GHz	835-1035nm	800MHz, 900MHz, 1800MHz, 1900MHz
Communication Range	< 100m	< 1000m	< 1000m(CALM IR)	< 15km
Mobility suitability	Low	High	Medium	High
Bit rate	6-54Mbps	3-27Mbps	$<$1Mbps,$<$2Mbps	$<$2Mbps
Transmission power for mobile node	100mW	2W EIRP (EU) 760mW (US)	12800 W/Sr pulse peak	380mW (UMTS) 2000mW (GSM)

technologies used in HetVANETs followed by the description of some applications for ITS.

- Various heterogeneous wireless access technologies exist in HetVANETs like 3G, 4G, LTE, LTE with D2D, 3GPP which cannot be easily well cooperated under the traditional VCN architectures. Consequently, a many of wireless network infrastructures and spectrum resources may be wasted thereby leading to the low quality of experience (QoE) for vehicle users. This situation may become worse with the increase in scale of network. It may increase the cost for network operators to deploy new services, as they need to configure or modify a large amount of underlying devices.

- The management and control of VCNs on large scale becomes an underlying bottleneck for performance of VCNs due to the ever increasing vehicular network size and highly evolved physical layer technology [3].
- Moreover, the handoffs between different cellular infrastructures in VCNs are more frequent due to intrinsic characteristics of VANETs (including high mobility and rapidly changing topology) as compared to traditional cellular networks.
- To provide consistency in services with the frequent topology changes and varying QoS demands in VCNs, the heterogeneous substrate cannot have a global view of all service requests, to make compromise and provide cooperation between all services. All the above aforementioned challenges of HetVANETs call for rethinking of current HetVANET architectures to support all network functionalities more efficiently on a large scale.

The following is a summary of advantages and challenges of candidate techniques (including cellular and DSR) in V2V and V2I modes for HeTVANETs;

1. V2I Communications
   - Advantages of LTE/LTE D2D
     - Large coverage
     - High downlink and uplink capacity
     - Centralized and flat architecture
     - Robust mechanism for mobility management
   - Challenges of LTE/LTE D2D
     - Lack of efficient scheduling schemes for ITS scenarios
     - Users in idle state cause high delay in disseminating messages

    - Easily overloaded in high density environments

- Advantages of DSRC
    - Low cost and easy deployment
    - Suitable for local message dissemination
- Challenges of DSRC
    - Serious channel congestion on large scale
    - Unbalanced link
    - Prioritization and service selection
    - Hidden node problems and broadcast storm

2. V2V Communications
    - Advantages of LTE/LTE D2D
        - High Spectrum Efficiency
        - High Energy Efficiency
        - Efficient resource Scheduling on D2D
    - Challenges of LTE/LTE D2D
        - Interference between D2D pairs and other users
        - Time consuming peer discovery
        - Performance degradation with high mobility
    - Advantages of DSRC
        - Ease of deployment and low cost
        - Ad-hoc mode
        - Low overhead
    - Challenges of DSRC
        - Serious channel congestion on large scale
        - Hidden node problems and Broadcast storm

2.3 Background and related work on 5G-Driven VANET Architectures

Heterogeneous vehicular networks have been regarded as a key enabling technology to meet various QoS requirements for future Intelligent Transportation Systems (ITS) services. However, conventional heterogeneous vehicular network architectures lack in flexibility on large scale as discussed in section. 2.2.6 and therefore, cannot efficiently deal with the increasing demands of data offloading over different access networks. SD-IoV is leading towards a potential solution to provide ubiquitous connectivity in integrated VCNs comprising of heterogeneous VCNs.

Data centres with millions of physical and virtual hosts are considered as a valuable resource for providing many services related to internet and cloud computing environments. To provide an efficient communication and cooperation on large scale VANETs, millions of vehicles are widely spread in the environment of Software Defined Internet of Vehicles (SD-IoV), where drivers and passengers can enjoy all ITS services through the internet. Moreover, future connected vehicles that are connected through IoV are playing an important role in ITS, by accommodating differentiated service requests and with different QoS requirements [3]. SD-IoV study has successfully demonstrated its superiorities to facilitate future ITS services [3]. There are several papers in which different solutions have been proposed for vehicular networks using the concepts of SDN and Internet of Vehicles (IoV) as cited in [35], [28], [36], [37], [38]. Due to its potential to solve different problems in vehicular scenarios as stated earlier, IoV is expected to be the potential solution to meet all the aforementioned challenges related to HetVANETs. Despite the efforts made in this field, this concept is still in its infancy and more refined and holistic architectures for Vehicular networks are expected in future.

2.3.1 5G-Driven Technologies

Software Defined Networking (SDN)

Software Defined Networking (SDN) is leading towards a revolutionary paradigm that is mainly differentiated due to separation of control and data plane with control plane having a centralized control, which dynamically defines forwarding rules in

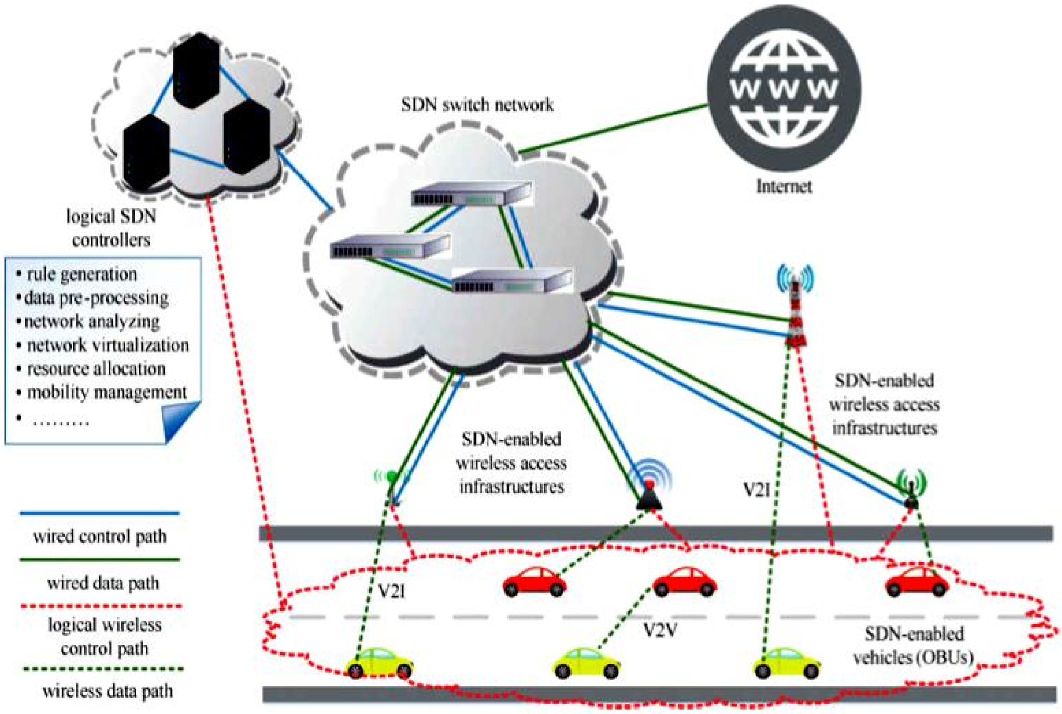

Figure 2.3: SD-IoV Architecture [3]

to switches in the data plane. Therefore, SDN helps in facilitating flexible network management and optimization on large scale with unified abstraction [3]. Additionally, network operators can also exploit the benefits of programmable SDN controller to easily configure network devices and quickly deploy new applications [39].

SDN Approach

The network consists of a set of white boxes (programmable Switches). One or more SDN controllers are connected to the white boxes via an out of band network. Control and management is performed via a separate interface. Switches become simple forwarding devices, obeying rules from the controller(s).

Current Networking Architectures: Limitations and Future Applications

- Each network device has to be configured separately using low-level and often vendor-specific commands which is prone to errors. Many configuration

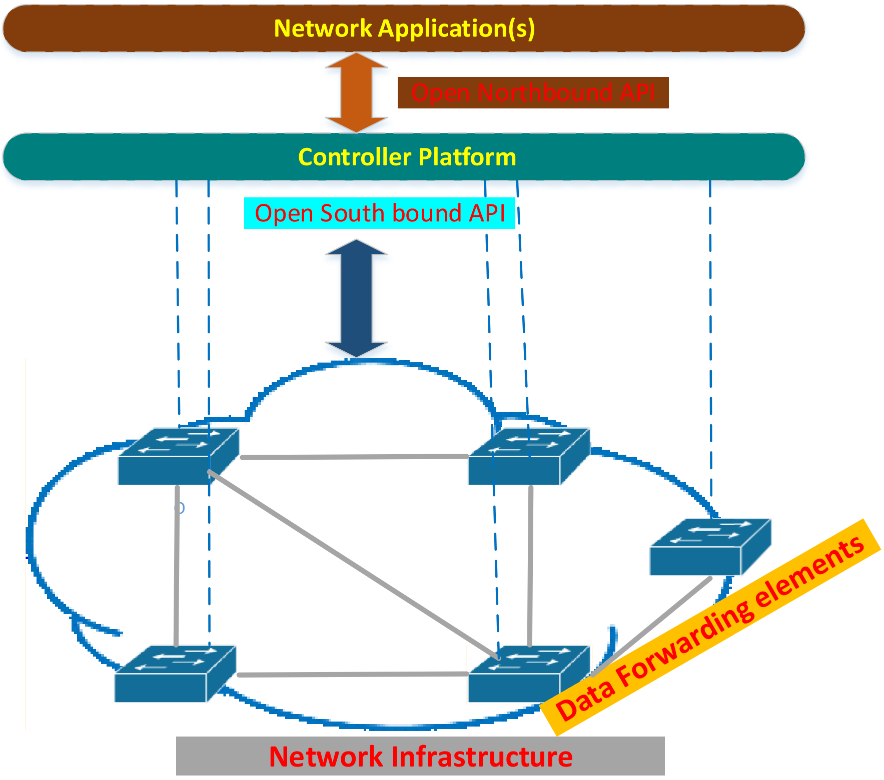

Figure 2.4: How will the network look like with SDN [4]

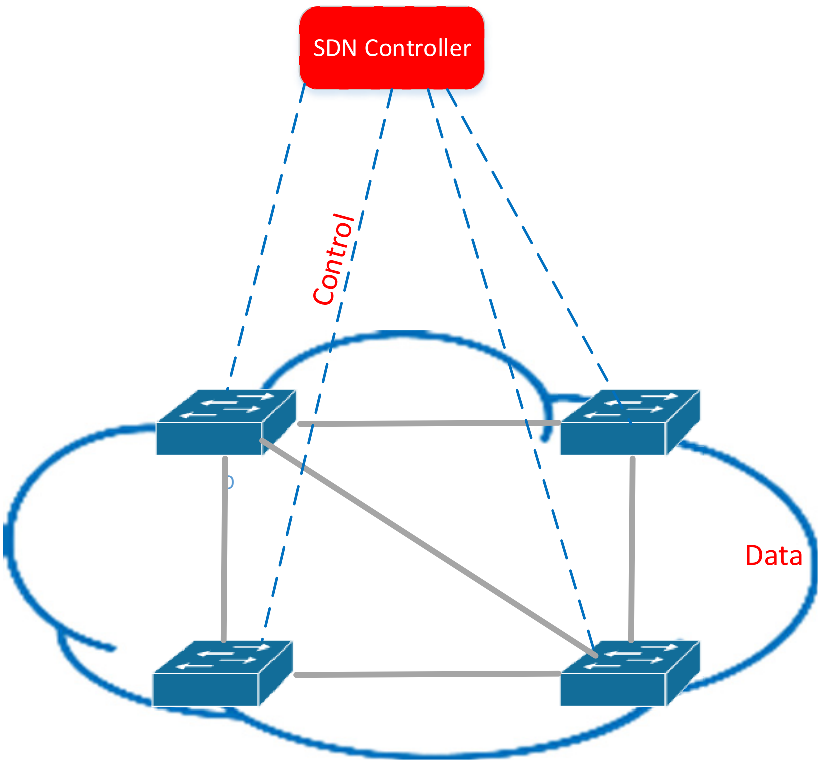

Figure 2.5: Centralized Control Plane

changes are done manually.

- Networking protocols are distributed among devices (switches, routers, firewalls and middle boxes).
- Many complex functions are embedded into the infrastructure
  - OSPF, BGP, NAT, TE, MPLS, Firewalls, multicast.
  - Redundant layer services
  - Unique differentiation
- Difficult to implement new protocols and features as it will change the control plane of all devices which are a part of topology or network.
- There is no common view of the network.
- Expensive network up gradation as new features are introduced via expensive and hard-to-configure equipment (aka middles boxes)
- Network capital costs have not been reducing fast enough and operational costs have been growing, putting excessive pressures on network operators.
- Networks continue to have serious known problems with security, robustness, manageability and mobility.
- Even vendors and third parties are not able to provide customized cost effective solutions to address their customers' needs.
- Need innovative ways to manage extremely large and dynamic networks.

Traditional Networks Versus Software Defined Networks

- The key difference is how SDNs handle data packets. In a traditional network, the way a switch handles an incoming data packet is written into its firmware.
- With SDNs, management becomes simpler and middle boxes services can be delivered as SDN controller applications

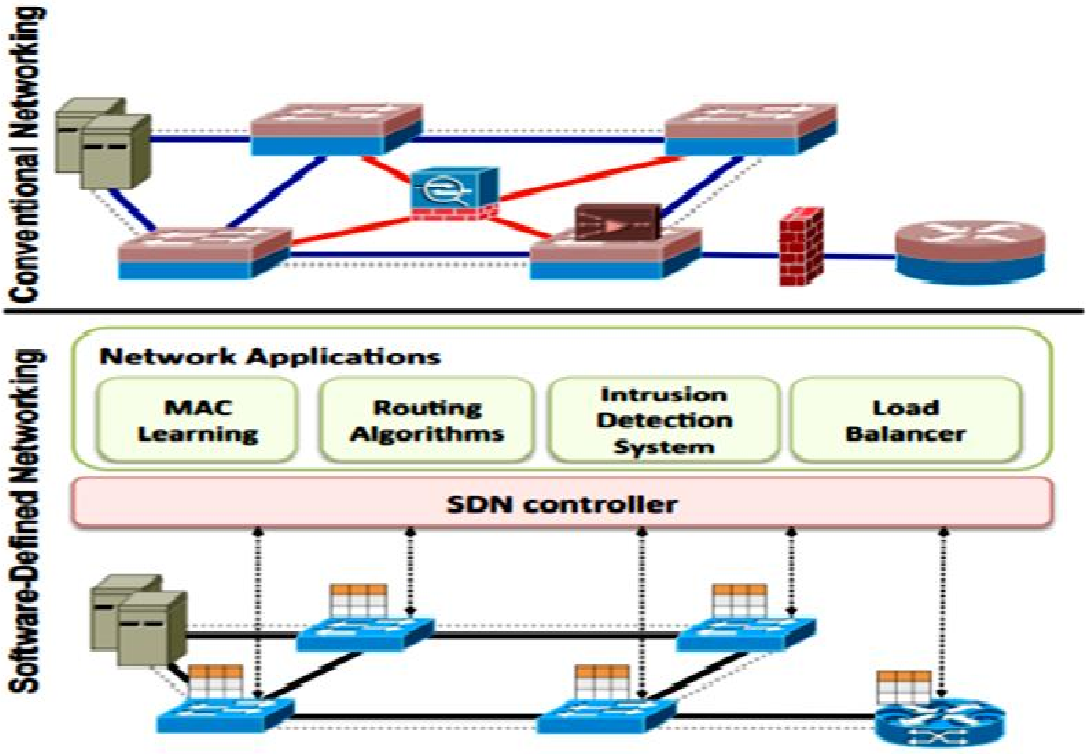

Figure 2.6: Traditional Networks Vs Software Defined Networks [4]

- Most switches particularly used in commercial data centres respond to and route all packets in the same way. SDN provides granular control over the way switches handle data, giving network administrators the ability to automatically prioritize or block certain types of packets.

- This technology allows for greater efficiency and control without the need to invest on expensive, application-specific network switches and devices.

SDN has been instigated in different network scenarios either theoretically, practically or experimentally due to its benefits of programmability and flexibility. The scenarios include, WLANs [40], wireless mesh networks [41], wireless sensor networks [42], cellular networks [43], narrow sense IoT [44] and wired data center networks [45].

2.3.2 Cloud Radio Access Network (C-RAN)

Recently, with the surge of mobile internet traffic, the mobile operators are facing difficulties in solving the pressure of ever-increasing capital expenditures (CapEx) and operating expenses (OpEx) with much less growth of revenue [46]. To facilitate rapid and inexpensive network deployments, the extensive computation resource offered by the cloud platform can be exploited. Cloud Radio Access Network (C-RAN) is expected to be a potential candidate of next generation radio access networks that can facilitate inexpensive network deployments [5]. The average revenue per user (ARPU) cannot catch up with the increasing expenditures, therefore, to meet user requirements the network operators must find new solutions to maintain a healthy profit and provide better QoS to customers. There are several ways to cope with the increasing traffic requirements in an energy-efficient way [5]. The first choice is to improve the efficiency of spectrum by employing more advanced transmission techniques like MIMO and beam forming. The second choice is to use Dynamic Spectrum Access technologies (DSA) such as, cognitive radio to exploit spectrum holes. However, these techniques cannot provide consistent and reliable services, and the increasing growth of data capacity is also limited. The third choice is to introduce more small sized cells and take full advantage of frequency reuse. However, this will cause more interference and there will be an increase in the operation and maintenance cost of deployed small cell infrastructure. Recently, there are multiple air interface standards introduced. Server-side cooperative-MIMO is used to facilitate rapid and inexpensive network deployments, by jointly processing geographically distributed base stations with overlapping coverage areas. This technique also helps in reducing complexity, size and power requirements of base stations that are geographically distributed.

Traditional Cellular Architecture

In the traditional cellular or Radio Access Network (RAN) architecture, there are many stand-alone base stations (BTS). Each BTS covers a small area, whereas a group of BTS provides coverage over a continuous area. Each BTS is responsible for radio and baseband processing functionalities and transmits its own signal to and from the mobile terminal, and forwards the data payload to and from the mobile-terminal and out to the core network via the backhaul. There are few limitations of traditional RAN architecture. Firstly, each BTS is costly to build and operate, as it has to perform all radio and baseband processing functionalities. Secondly, when

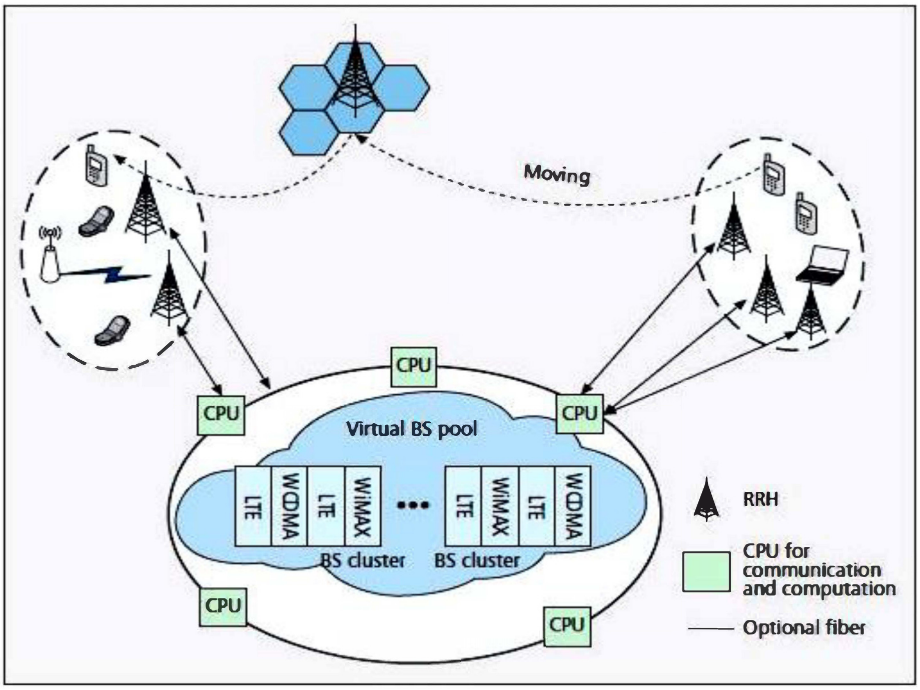

Figure 2.7: Cloud RAN Infrastructure [5]

more BTS are added to a system to improve the capacity, interference among BTS becomes more severe as BTS are closer to each other and most of them are using the same frequency. Thirdly, the traffic of each BTS is continuously fluctuating (called 'tide effect') due to mobility of users. Consequently, the average utilization rate of individual BTS becomes lower. However, these processing resources cannot be shared with other BTS. Therefore, all BTS are designed to handle the maximum traffic, not the average traffic that results in wastage of resources and power at times when there is no traffic or the system is idle. There is an antenna that is generally located within the proximity of few meters of the radio module as shown in Fig.2.8 as coaxial cables that are used to connect them exhibit high losses. X2 interface is defined between base stations, S1 interface connects a base station with mobile core network. This architecture was popular for 1G and 2G mobile cellular networks.

Base Station with RRH

This architecture was introduced when 3G networks were being deployed and recently it is used by majority of base stations. In a base station with Remote Radio Head (RRH) architecture, each base station is divided into two parts as shown in Fig. 2.9.

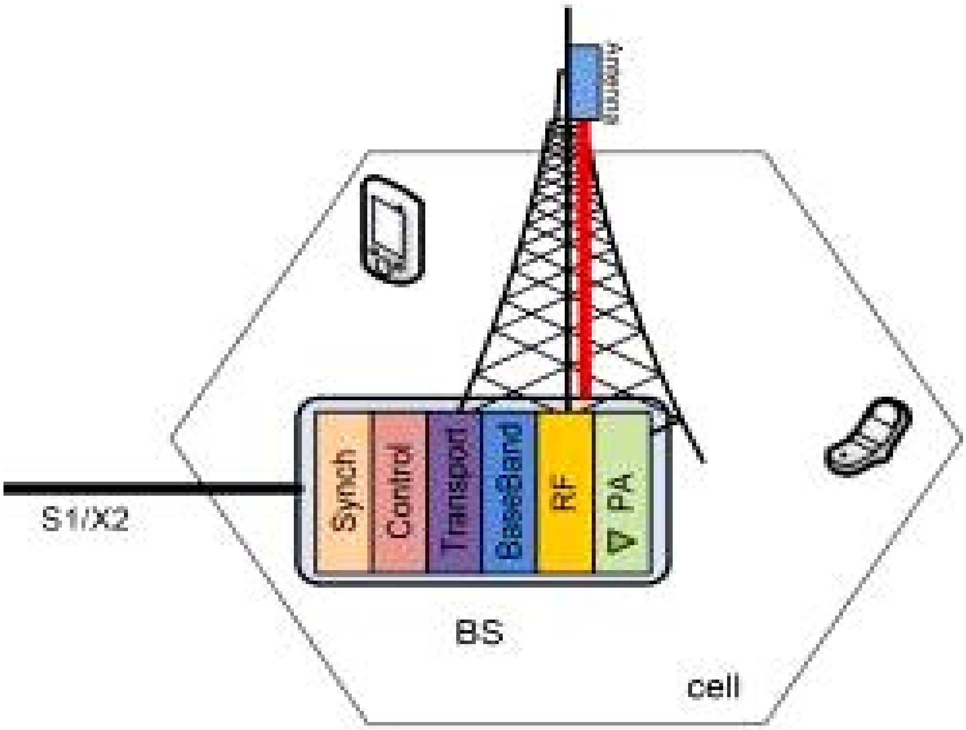

Figure 2.8: Traditional cellular architecture [6]

- **RRH or Remote Radio Unit (RRU):** RRH provides the interface to the fiber and performs different functions like digital processing, digital to analog conversion, analog to digital conversion, power amplification and filtering [47].

- **BBU or Data Unit (DU):** The baseband signal processing part is called a Base Band Unit (BBU) or Data Unit (DU). The distance between a RRH and a BBU can be extended up to 40 km. Optical fiber and microwave connections can be used between RRHs an BBUs. One BBU can serve many RRHs. Compared to cellular traditional architecture, where a BBU needs to be placed close to the antenna, the BBU equipment is placed in a more convenient and easily accessible place thus reducing cost for site rental and maintenance. RRHs are statically assigned to BBUs that is similar to the traditional cellular or RAN architecture. RRHs can even be placed up on poles or rooftops. RRHs can be connected to each other in a daisy chained architecture.

  Common Public Radio Interface (CPRI): RRH is connected to BBU by Common Public Radio Interface (CPRI) interface. CPRI is the radio interface protocol widely used for IQ data transmission between RRHs and BBUs on Ir interface [48]. It is a constant bit rate, bidirectional protocol that requires accurate synchronization and strict latency control between RRH and BBU. Other recommended protocols are the Open Base Station Architecture Initiative (OBSAI) [49] and Open Radio equipment Interface (ORI) [50].

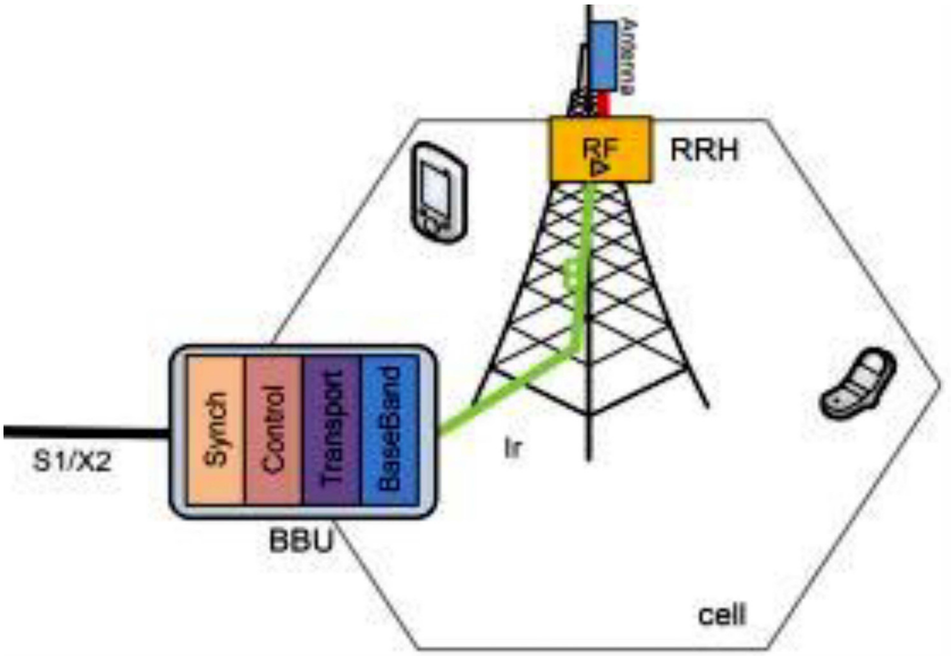

Figure 2.9: Base Station with RRH [6]

C-RAN Architecture

Cloud Radio Access Network (C-RAN) is a novel mobile network architecture where baseband resources are pooled, so that they can be shared between base stations. C-RAN is basically designed to be applicable to most typical RAN scenarios that is from macro cell to femtocell as shown in Fig. 2.7. C-RAN has the following components [5], [6];

- **Baseband Unit (BBU):** The BBU acts as a digital unit that is responsible for implementing the base station functionalities from baseband processing to packet processing. Several BBUs are placed in a central physical pool to distribute RRHs according to RF strategies. Using the BBU pool, network operators can dynamically deploy real-time virtualization technology that maps radio signals from/to one RRH to any BBU processing entity in the pool.

- **Remote Radio Head (RRH):** RRHs are responsible for performing radio functions, including frequency conversion, amplification, and A/D and D/A conversion. The RRHs also send and receive digital signals to and from the BBU pool via optical fiber. Moreover, antennas are equipped with RRHs to transmit and receive radio frequency (RF) signals.

- **Optical Transmission Network (OTN):** Optical Transmission Network (OTN) is responsible for transmitting and receiving digital signals to and from the BBU pool via optical fiber.

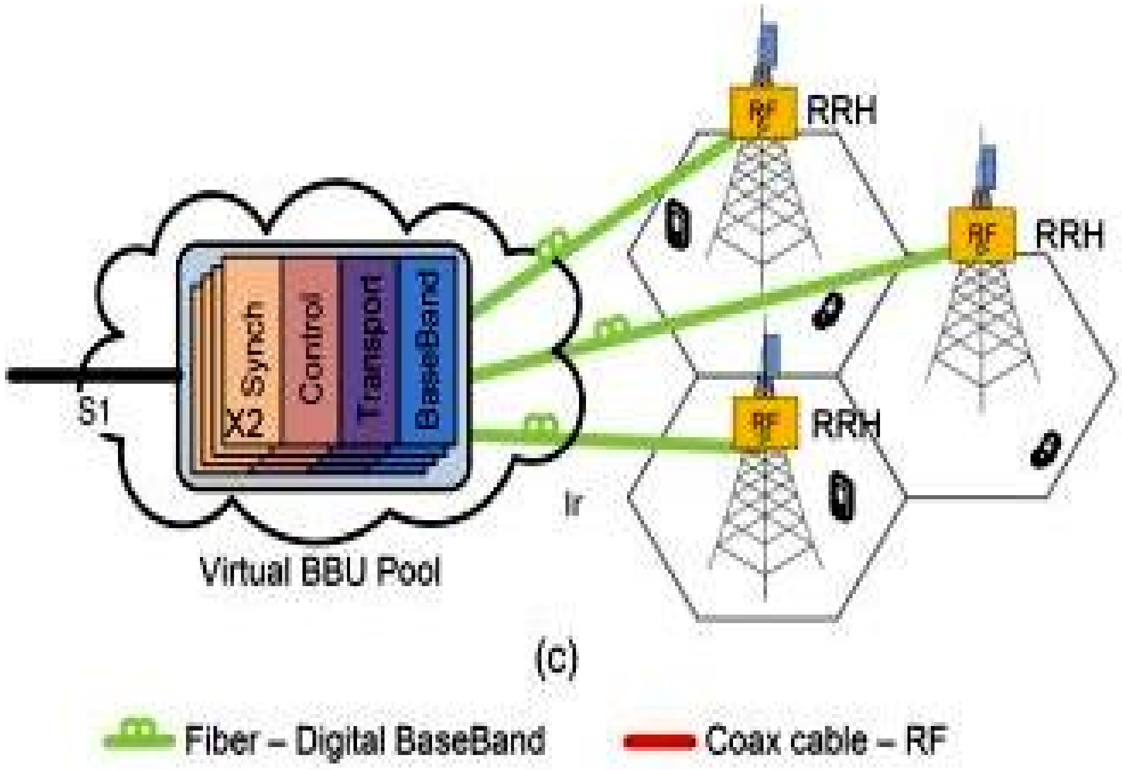

Figure 2.10: Cloud RAN with RRH [6]

The following are the benefits of C-RAN [5];

- **Reduces Cost:** It allows pooling the Baseband Units (BBUs) by aggregating multiple base stations into a centralized BBU Pool, thus offering statistical multiplexing gain by shifting the burden to the high-speed wireline transmission of In-phase and Quadrature (IQ) data. All the computational resources are aggregated in a few big rooms, and are managed centrally and leaves simpler functions in RRHs.

- **Improved Energy Efficiency:** All processing functionalities of BSs are embedded in a remote data-center. As a result, C-RAN reduces the burden on base stations by dynamically allocating baseband functionaries in a BBU pool by introducing energy efficient network operations. Power consumption can also be reduced by dynamically allocating processing capability tasks between BSs and also performing some migrating tasks between different BSs in a centralized BBU pool. Several BSs can be turned to low power or even be shut down remotely in a BBU pool. Moreover, C-RAN architecture has made it very convenient and cost effective for network operators to cover more service areas or split the cell for higher capacity. Therefore, they only need to install new RRHs that connect with the BBU pool.

- **Better Spectrum utilization:** C-RAN also improves network capacity by performing load balancing and cooperative processing of signals originating from several base stations. C-RAN allows sharing of Channel State Information (CSI) of each Base station-mobile station BS-MS link, traffic data and control information of mobile services among cooperating BSs. Consequently, by using multipoint cooperation in this scheme, the system capacity is improved, as more streams are multiplexed on the same channel with little or no mutual interference.

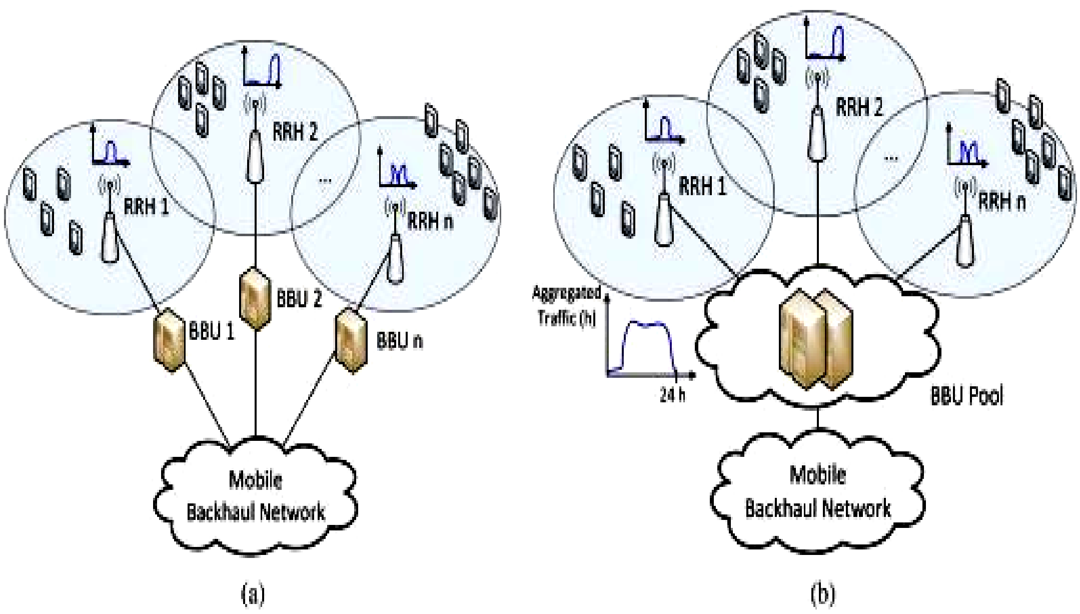

Figure 2.11: Cloud RAN architecture for mobile networks [6]

To address flexible network control, optimization and efficient data offloading in heterogeneous Vehicular Ad hoc Networks (HetVANETs) on large scale, the centralization and flexibility of Cloud Radio Access Network (C-RAN) and Software Defined Networking (SDN) can be integrated with Network Function Virtualization (NFV) to support the dynamic nature of HetVANETs where multi domain resources (like video streaming file downloading, Web browsing and others.) can also be exploited to support future ITS applications. Interoperability among different co-existing wireless infrastructure can also provided using C-RAN.

2.3.3 Network Function Virtualization(NFV)

The rapidly growing market demands have posed many challenges to the traditional mobile broadband network architectures. On one hand, it is becoming difficult to accommodate exponentially growing amount of network equipment of operators by using limited machine room space. On the other hand, the heterogeneity caused by different specifications of wireless access equipment has triggering many problems related to management and optimization of networks [2]. Network function virtualization (NFV) is recently proposed to improve the flexibility of network service provisioning [51]. The idea of NFV is proposed along with other emerging technologies, such as software defined networking (SDN) and cloud computing to solve many problems caused due to the proprietary nature of existing hardware appliances. NFV decouples the software implementation of network functions from the underlying hardware and it has the potential to lead to significant reductions in operating expenses (OpEx) and capital expenses (CapEx). This technology is still emerging and there are lot of opportunities for researchers to develop new architectures and applications and to evaluate design trade-offs in emerging technologies for its successful deployment. Moreover, this technology also facilitates the deployment of new services with increased agility and faster time-to-value [7]. Some of the future challenges for the deployment of NFV include the guaranteed performance of networks for virtual appliances, their dynamic instantiation and migration as well as their efficient placement.

It is well known that bringing new services into today's networks is becoming difficult day by day due to the proprietary nature of existing hardware devices. This task does not only require highly and rapidly changing skills of professionals to operate, manage and integrate these devices, but also requires dense deployments of network equipment. NFV has been proposed to address all these challenges in an innovative way to design, deploy and manage networking services by leveraging virtualization technology. The main idea of NFV is to decouple the physical network equipment from the functions that run on them [7]. The architecture we propose is based on in-

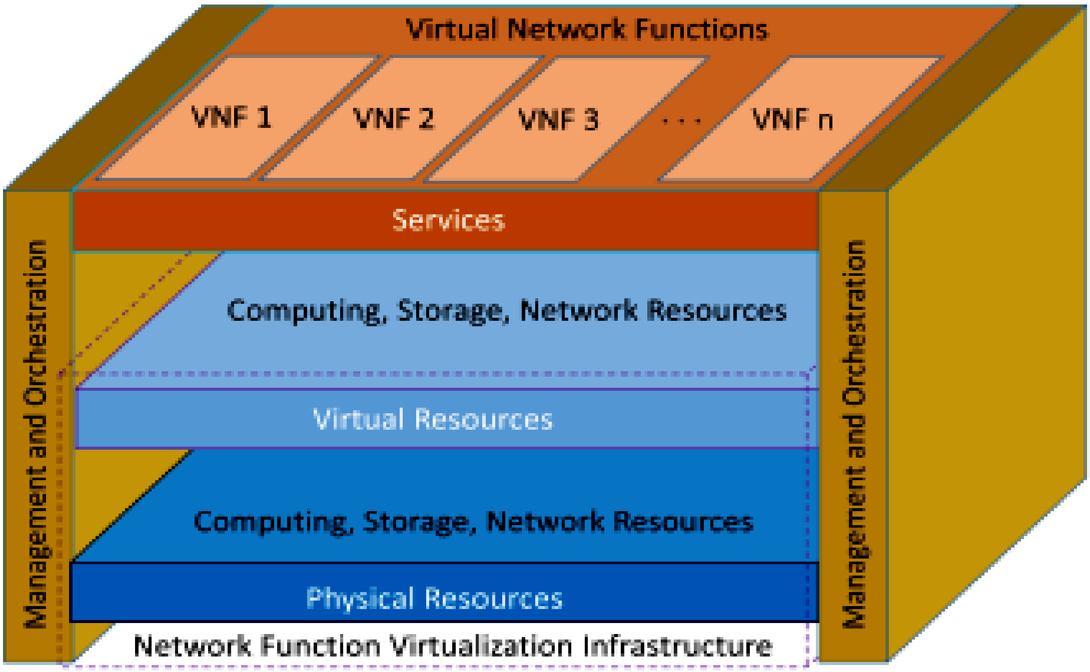

Figure 2.12: FV Infrastructure [7]

tegrating the centralization and flexibility of SDN and C-RAN with NFV to support the dynamic nature of Heterogeneous HetVANETs to support future ITS applications. Fig. 2.13 shows the relationship between SDR, SDN and NFV. Recently Network Function Virtualization (NFV) has also emerged as a way to decouple software implementation of network functions from the underlying hardware and enable software to run in a virtualized environment. This improves the flexibility of network service provisioning [52] and facilitates the deployment of new services with increased agility and faster time-to-value. Nevertheless, current VANET architectures cannot meet the latency requirements of future ITS applications in highly congested and mobile scenarios. The future trend of autonomous vehicles drives current VANET architectures, broadening their limits with challenging real-time requirements. In addition, the maturity of cloud computing has adapted the in-

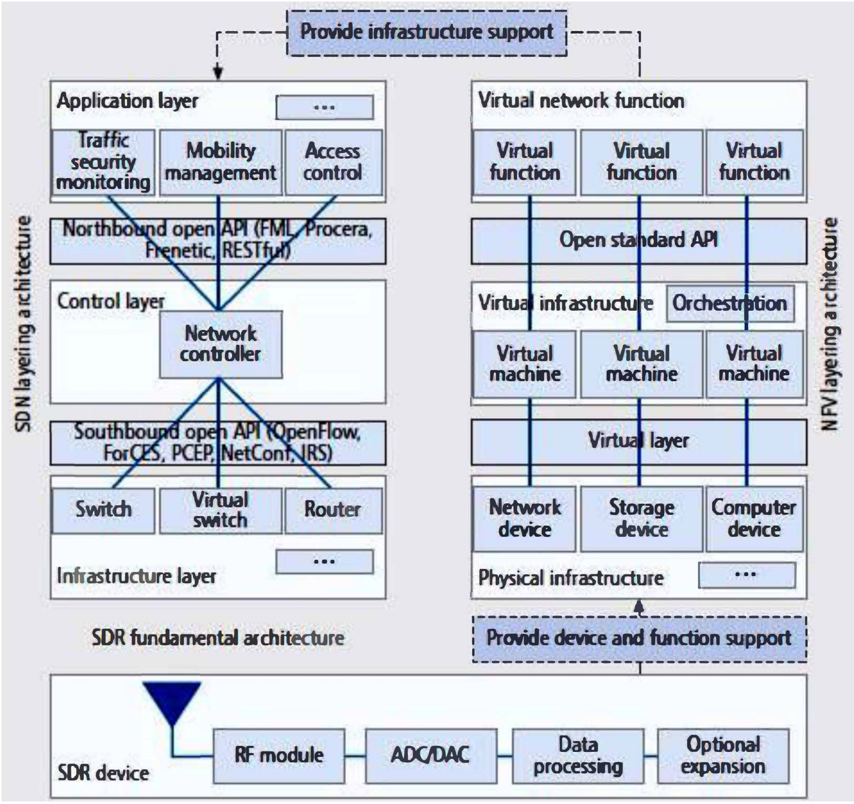

Figure 2.13: Architecture showing integration of NFV, SDR and SDN [2]

vasion of vehicular space with cloud-based services. The cloudification of network resources through SDN and C-RAN is another promising enabler for 5G Next generation vehicular networks. SDN is leading towards a revolutionary paradigm which controls the network in a centralized and programmable manner by decoupling the forwarding functions (data plane) and network controls (control plane). Moreover, due to its potential to offer flexibility, programmability and centralized knowledge, it facilitates flexible network management and control on large scale, with unified abstraction [13], [2], [14].

2.4 Conclusion

A comprehensive literature review is presented explaining the features and challenges of Vehicular Ad-hoc Networks (VANETs) comprising of heterogeneous infrastructures such as cellular (3G, 4G, LTE, 5G, LTE D2D, 3GPP) and IEEE 802.11p/DSRC. Furthermore, some challenges of current Vehicular Communication Networks (VCNs) including heterogeneous Vehicular Ad-hoc network (HetVANETs) are also explained in detail. Current Vehicular Ad-hoc Network architectures utilising 5G-driven technologies are also discussed.

Different 5G-driven technologies including Software Defined Networking (SDN), Cloud-Radio Access Network (C-RAN), Network Function Virtualization (NFV) are also presented including their advantages and disadvantages. Furthermore, traditional networks are also discussed with 5G driven technologies including including their limitations and future applications to highlight the importance of 5G-driven architectures.

Chapter 3

5G Next generation VANETs using SDN and Fog Computing Framework

3.1 Introduction

The growth of technical revolution towards 5G next generation networks is expected to meet the various communication requirements of the future Intelligent Transportation Systems (ITS). Motivated by the consumer needs for variety of the ITS applications, researches are currently exploring different network architectures and techniques, which could be employed in the next generation ITS. In recent years, VANETs are rapidly evolving. The number of connected vehicles is predicted to reach 250 million, by 2020 [53]. Moreover, by 2020, smarter and secure ITS are expected to be operational as a VANET cloud [54]. Nevertheless, current VANET architectures can not meet the latency requirements of future ITS applications in highly congested and mobile scenarios. The future trend of autonomous vehicles drives the current VANET architectures, broaden their limits with hard real-time requirements.

This main objective of this chapter is to present a new hierarchical 5G next generation VANET architecture to provide flexible network management, control and high resource utilization in the VANETs on a large scale. The key idea of this holistic architecture is to integrate the centralization and flexibility of Software De-

fined Networking (SDN) and Cloud-RAN (C-RAN), with the 5G communication technologies, to effectively allocate resources with a global view. Moreover, a fog computing framework (comprising of zones and clusters) has been proposed at the edge, to avoid frequent handovers between the vehicles and the RSUs.
The major contributions and results of this chapter can be summarized as follows;

- A new hierarchical 5G next generation VANET architecture is proposed, utilising the idea of SDN, C-RAN and the fog computing technologies.
- To support vehicles and end users with prompt responses, a new Fog Computing (FC) framework is proposed at the edge of network. The details of FC framework are discussed further.
- The control functionality deployment of controller is divided in a hierarchical manner to reduce control overhead on the centralised controller.
- The transmission delay, throughput and control overhead on the controller are also analyzed and compared with other architectures. Simulation results reveal the minimized transmission delay and control overhead on the controller, considering different vehicle densities.
- Moreover, the throughput of proposed architecture is also analyzed, using average bandwidth allocation scheme and adaptive bandwidth allocation scheme (i.e., by keeping in view different bandwidth demands of users). Simulation results reveal the improved throughput.

The rest of the chapter is organized as follows. In section 3.2, background and some related work is presented, to describe the motivations towards the 5G enabler technologies for the VANETs. Section 3.3 describes the topology and logical structure of architecture. In section 3.5, the performance of proposed architecture is analyzed and compared with the other architectures. Finally, the work is concluded.

3.2 Background and Related Work

Due to high mobility and rapidly changing topology of VANETs, it is difficult to realize next generation ITS services by using a single wireless infrastructure. Extensive research and efforts have been made from both industry and academia, in the field of next generation Vehicular Communication Networks (VCNs), to get Smart Vehicles connected with the surrounding vehicles, road-side infrastructures, and internet through different wireless communication infrastructures [27], [28]. Therefore, next generation vehicular networking is expected to adopt current cellular solutions such as 4G Long Term Evolution (LTE), 3GPP, and is expected to be heterogeneous in terms of resources and network topology. LTE systems offer the benefits of large coverage, high throughput and low latency [32]. However, due to high vehicle mobility and dynamic network topology, it is relatively challenging to provide satisfied ITS services only through LTE systems. Integrating different access networks technologies like DSRC and LTE, is proposed to be a potential solution to meet various ITS service requirements [27]. However, building heterogeneous vehicular networks (integrating IEEE 802.11p with cellular technologies like 3G, 4G/LTE systems) requires a deep understanding of heterogeneity and its associated challenges in VANETs. Due to high mobility and rapidly changing topology of VANETs, the handoffs among different wireless access infrastructures are more frequent, as compared to traditional wireless networks thus causing service interruptions. There is a need to develop some unified ways to deal with control and management issues rising in heterogeneous VANETs on large scale. Furthermore, to provide consistency in services with the frequent topology changes and varying QoS demands in VANETs, the heterogeneous substrate cannot have a global view of all service requests, to make compromise and provide cooperation between all services. Inspite of all the efforts made in the field of heterogeneous VANETs, there is still a dramatic gap between the practical requirements of ITS services and what can be offered by existing heterogeneous VANETs. All of these issues above, call for rethink of the current network architecture for VANETs. Consequently, the research and development for the fifth generation (5G) systems have already been started [55], [56], [2], [14], [57], [58], [59], [60], [61]. On the other hand, SDN has been proposed as a promising technique that will play a key role in the design of 5G wireless communication networks [14]. SDN is proposed to be an effective technology to be capable of supporting the dynamic nature of VANETs and ITS applications, by facilitating flexible network management and optimization on large scale with unified abstraction [13]. In order to meet the demanding requirements of future ITS, SDN, Cloud Computing, Fog Computing are expected to be future candidate technologies for 5G VANETs. Some initial studies have also been carried out to integrate either of these technologies into Vehicular Communication Networks [13], [10], [38]-[62]. Nevertheless, the performance of SDN technology becomes limited in RSUs, when the number of vehicles connected with RSU increases [38]. The frequent handover problem in dense scenarios of VANETs, reduces the performance of SDN at RSUs [63]. However, it is also realised that the scalability of Wireless Distributed Networks (WDNs) is improved by using techniques like; clustering, multichannel routing and zoning [22] and [64].

Nowadays, C-RAN has been widely accepted to be a promising solution for heterogeneous networks [10]. In C-RAN, all RAN functionalities are performed in the centralized BBU pool, in cloud based infrastructure, which are connected to RRHs via fibre. The separation between the data plane and control plane via SDN can be built upon the open platform of Cloud-RAN by keeping in view the service demands of different users, thus reducing operational cost. In this chapter, a hierarchical 5G next- generation VANET architecture is proposed by employing the concepts of SDN, C-RAN and fog computing as shown in Fig. 3.1.

3.3 5G next generation VANET Architecture

3.3.1 Topology Structure of Fog Computing (FC) Framework, C-RAN and the SDN controller:

To support vehicles and end users with prompt responses, FC framework is configured at the edge of network. FC framework is comprised of the following components;

- **Fog Computing-Zone Controllers (FC-ZCs):** The FC-ZCs are the computing enhanced (i.e., CPU and storage) wireless access infrastructures such as, RSUs, Base Stations (BSs) connected with the BBU controllers, through broadband connections. In our case, a *zone* is defined as a group of vehicles that is registered with one RSU or a BS. Therefore, one FC-ZC is responsible for controlling one zone. Most of the data at edge is processed and saved by

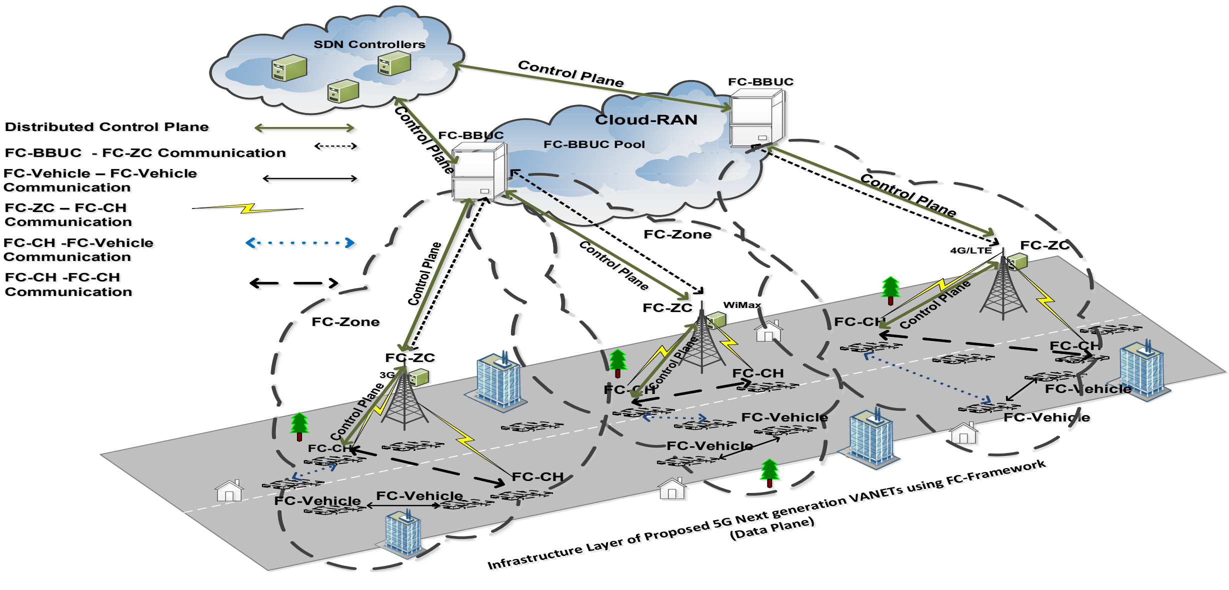

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Figure 3.1: Topology Structure of 5G next generation VANETs using SDN and Fog Computing (FC) Framework

FC-ZCs. Moreover, FC-ZC devices are SDN- enabled, meaning they are under the control of SDN controller. SDN controller can control functionalities such as, packet forwarding, and transmitting, as well as operations related to infrastructures such as, power control, channel assignment and resource allocation. SDN controller collects and forwards the state information of FC-ZCs into the C-RAN, via Fog Computing BBU Controllers. The control overhead of vehicles remains in their own vicinity i.e., FC-zones or FC-Clusters, and is not sent to the SDN controller, unless required. Hence, FC-ZCs and FC-zones play an important role in minimizing the overhead in the control plane. These devices act as both control pane and data plane elements.

- **Fog Computing-Cluster-heads (FC-CHs:)** Further, FC-zones are divided into Fog Computing-Cluster heads (FC-CHs. Each FC-CH is controlled and managed by FC-ZC. FC-CHs are the vehicles, equipped with SDN-enabled On Board Units (OBUs). The potential functionalities of OBUs include, packet forwarding, power control, channel selection, interface selection and transmission mode (i.e, V2V or V2I communication). FC-CHs are also control plane and data plane elements. FC-CHs collects and forwards the state information of FC-Vehicles within a FC-ZCs.

- **Fog Computing-Vehicles (FC-Vehicles):** FC-Vehicles act as end users, and are also equipped with SDN-enabled OBUs. The potential functionalities of OBUs include, packet forwarding, sensor localization system like Global Positioning system (GPS), power control, channel selection, interface selection and transmission mode (i.e, V2V or V2I communication). Moreover these OBUs are also equipped with radio transceivers for Wireless Access in Vehicular Environment (WAVE) and other wide-range radio transceivers such as, 3G/4G/LTE for communication with cellular BSS.

- **Fog Computing BBU Controllers (FC-BBUCs):** FC-BBUC connects mutiple FC-ZCs with the backhual links. The FC-BBUC acts a as digital unit that is responsible for implementing the base station functionalities, from baseband processing to packet processing. Several FC-BBUCs are placed in a central physical pool, to distribute FC-ZCs according to RF strategies. The advantage of using SDN-based virtualization for C-RAN, in our proposed framework is that resource allocation and scheduling can be effectively and simply managed by the central controller, with a global view. Therefore, FC-BBUCs act as a bridge, connecting VANET infrastructure with the SDN controller. The FC-BBUC collects the state information of different FC-ZCs connected with it, and by using its own local intelligence, it can make forwarding decisions, thus reducing the overhead on centralised controller. FC-ZC will communicate with the FC-BBUC, for inter FC-zone communication. Therefore, FC-BBUCs are the data plane as well as control plane devices.

- **SDN Controller:** As a core component, SDN controllers are responsible for network management and operations such as, rule generation, resource allocation and mobility management. Moreover, they can also perform some advanced network functionalities like, learning, network analysis and data preprocessing. In our case, SDN functionalities are distributed and also shared among local controllers i.e., FC-ZCs and FC-BBUCs and FC-CHs in a hierarchical manner. Moreover, the SDN controller is also responsible for Fog Orchestration and resource management of fog.

- **Optical Transmission Network (OTN):** Optical Transmission Network

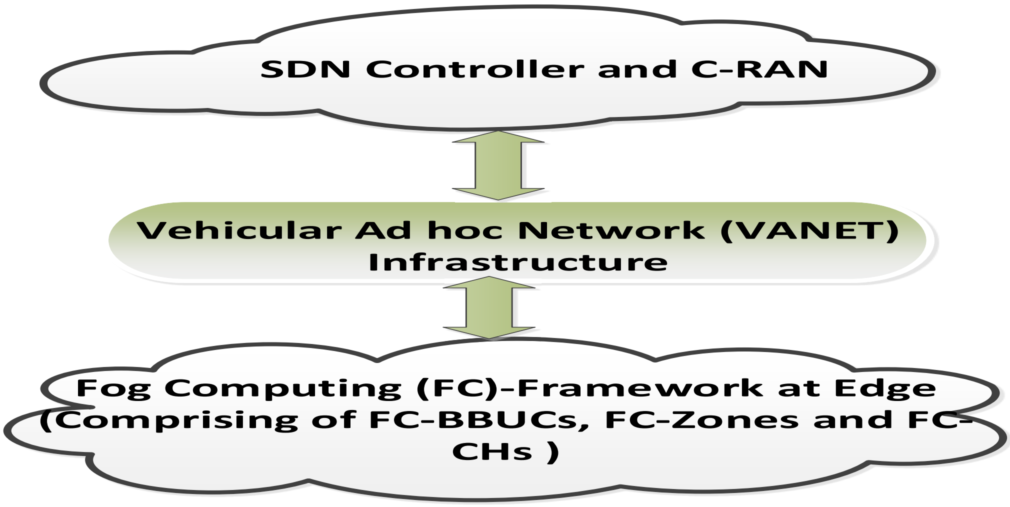


Figure 3.2: Hierarchy of SDN controller, Cloud-RAN and Fog computing framework

(OTN) is responsible for transmitting and receiving digital signals to and from the FC-BBUC pool via optical fiber. The FC-ZCs send and receive digital signals to and from the FC-BBUC pool via optical fiber.

3.3.2 Logical Structure of proposed 5G next generation VANET architecture:

The logical structure of proposed architecture is divided into data plane, control plane and application plane as shown in Fig. 3.3. The data plane includes FC-Vehicles, FC-CHs, FC-ZCs and FC-BBUCs. Functionalities include data collection, quantization and then forwarding data to the control plane [65], [37]. The data plane devices can be configured in to the following function modules;

- ***Information gathering module of FC-Vehicles, FC-CHs, FC-ZCs, FC-BBUC***: This module uses different sensors to record information related to position, speed and direction of vehicles and CCTVs, network cameras, lane checking cameras.
- ***Communication module of FC-Vehicles, FC-CHs, FC-ZCs, FC-BBUCs:*** This module further includes V2V and V2I communication module. V2V provides wireless communication between two adjacent vehicles, that may

be two FC-Vehicles or two FC-CHs or a FC-CH and a FC-Vehicle, by using WiFi/WAVE. V2I communication provides wireless communication between FC-CHs and FC-ZCs. Further, the communication module of FC-BBUCs includes two types of communication modules, one is between FC-BBUC to FC-ZC and, other module is between FC-BBUC to SDN controller. Furthermore, inter-(FC-ZCs) and inter-(FC-BBUCs) communication is also performed by this module.

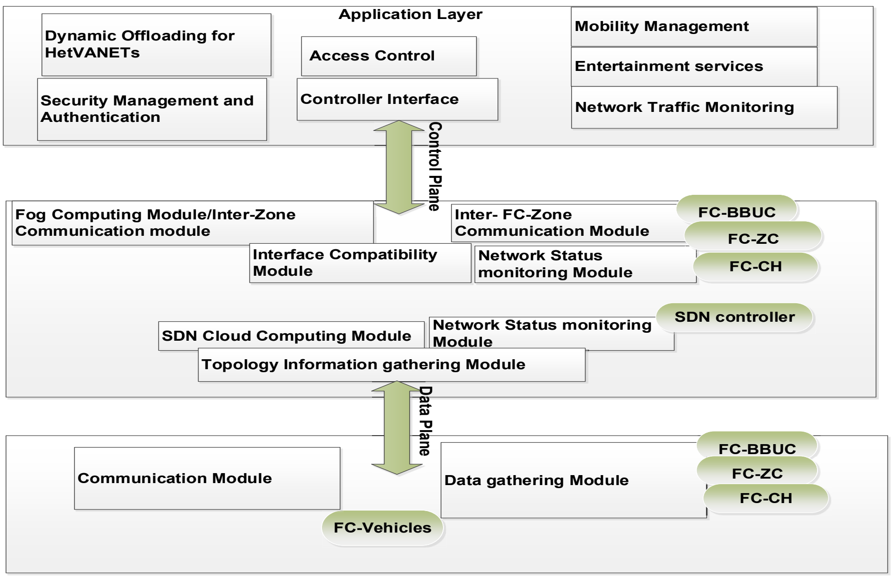


Figure 3.3: Logical Structure of proposed 5G next generation VANETs

The control level of SDN decides the flow rules or policy rules [66]. Since, we are using fog architecture at edge, therefore, the SDN controller will operate in Hybrid Control Mode as shown in Fig. 3.1 and 3.2. The control plane includes SDN controllers, FC-BBUCs, FC-ZCs and FC-CHs. The FC-BBUC is the main control center or *fog controller* of fog framework. SDN controller functionalities are shared at the edge of network, between FC-BBUC, FC-ZCs and FC-CHs. The SDN controller will not take full control of the network. Instead of sending specific flow rules, the SDN controller will send abstract policy rule. The specific behaviour of policy rules will be decided by FC-ZCs, FC-BBUCs and FC-CHs, depending on their own local intelligence [35]. Following are the control plane function modules;

- ***Information gathering modules of FC-BBUC, FC-ZCs and FC-CHs:*** To draw global view map of network, based on data information provided by the data plane.

- ***Computing and Storage modules:*** These modules are deployed in fog computing framework devices and cloud computing centres.

- ***Network status monitoring module:*** Responsible for monitoring the links of 5G SDN-based VANET architecture.

- ***Inter-FC-zone communication module:*** Configured in FC-ZCs to provide inter zone communication in fog network.

- ***Inter-FC-BBUC communication module:*** Configured in FC-BBUCs to provide inter BBU communication in Cloud-RAN.

- ***Intra-FC-zone communication module:*** Configured in FC-CHs to provide communication between FC-CHs within a FC-Zone.

The application plane is responsible for generating rules and strategies, based on different application requirements of users/vehicles, and forward these rules to the control plane. Details are in Fig. 3.3. Table 3.1 shows some of the requirements of proposed architecture using Cloud computing (SDN controller cloud and C-RAN) and fog computing framework.

3.4 Simulation Methodology

The performance of proposed architecture is investigated, by analysing the throughput, transmission delay, and control overhead on controllers, using MATLAB. Some simulation set-up details are presented in Table 3.2. All bandwidths are averagely assigned by FC-ZC, to vehicles within a zone. However, every vehicle needs different bandwidths in practical ITS scenarios and applications. Considering the real bandwidth requirements of vehicles, an adaptive bandwidth allocation scheme is also used to optimize the throughput of fog framework.

Table 3.1: Requirements of Proposed architecture

Requirements	**Cloud Computing framework (C-RAN and the SDN controller)**	**Fog Computing Framework**
Mobility Support	Limited	Supported
Geographical Distribution	Centralised and Distributed	Centralised and Distributed
Security	Undefined	Can be Defined
Location of Server Nodes	Within internet	Edge Network
Distance between vehicle and servers	multiple hops	single hop/very few hops
Location Awareness	No	Yes
Delay	High	Very Low
Control functionality deployment	Hierarchical	Hierarchical
Controller Operation Mode	Hybrid (shared between Fog computing devices and the SDN controller)	Hybrid (shared between zone controllers and CHs)

Parameters	Values
Transmission range	100m
RSU range	570m
No. Of Vehicles	10, 20, 30, 40, 50, 60
Transmit power	24dBm
Receiver Sensitivity	-80dBm
RSU range	570m
Time per slot	0.5 ms
Bw	100 Mbps
No. of RSUs	9
Clustering	ALM [8]

Table 3.2: Simulation parameters

3.5 Comparison of Throughput, Transmission delay and Control overhead on controllers

The performance of our proposed architecture is analyzed and compared with two architectures i.e., traditional architecture and 5G VANET architecture proposed in [67], named as 5G SD VANETs for our comparison. In traditional architecture, every vehicle communicates with the RSU directly, whereas in [67], each node has to send signalling information to a node closer to RSU. The performance of proposed architecture is investigated, by analysing the throughput, transmission delay, and control overhead on controllers, using MATLAB.

Considering the real bandwidth requirements of vehicles, an adaptive bandwidth allocation scheme is also used to optimize the throughput of fog framework. Simulation results in Fig. 3.4 show improved throughput, as compared to throughput in [67], and throughput of traditional architecture. It is shown in Fig. 3.5 that the throughput of a FC framework using both average and adaptive bandwidth allocation scheme is improved as compared to throughput of fog cell in [67]. We analyse and compare the transmission delay of vehicle, in fog framework, considering different vehicle densities. In [67], as the complexity of handovers between vehicles and RSU is increased, with an increase in multihop relay vehicles, the propagation delay

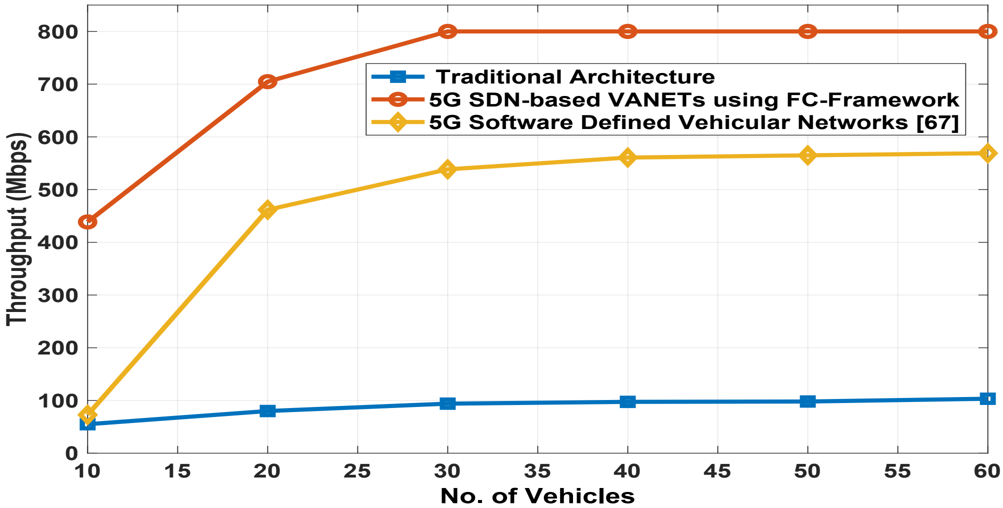


Figure 3.4: Throughput Comparison

increases. Using the concept of zones and clusters, the number of multihop relay vehicles is reduced, thus reducing delay. For analysis, we use ALM [8], as a clustering strategy. Fig. 3.6 shows, there exist a minimum transmission delay of $0.06ms$, as compared to transmission delay of traditional architecture and 5G Software Defined Vehicular Networks architecture [67]. The reason is, in our proposed FC-Framework, the control functionalities are divided among different controllers and data processing and applications are concentrated in devices/vehicles at the network edge, rather than existing almost entirely in the cloud. Moreover, devices/vehicles communicate peer-to-peer to efficiently share/store data and take local decisions, thus reducing delay. Another reason is that due to more than one FC-CHs within FC-zones, the FC-CHs are directly communicating with the RSUs, thus reducing number of relay hops for transmission and reducing delay. It is also seen that, when the density of vehicles is low, the distance among adjacent vehicles is far away, therefore, the success transmission probability of link is low, thus, delay will be increased. Increasing vehicle density, will decrease the distance among adjacent vehicles and therefore, the success of transmission probability will be increased. Therefore, delay will be minimized. We also analyse the control overhead on controllers. Fig. 3.7 shows that the control overhead on controller is significantly reduced as compared to the control overhead on controller using traditional architecture and 5G Software Defined Vehicular Networks architecture in [67]. This is due to hierarchical distribution of controllers in control plane, and practical use of zones and clusters in our proposed

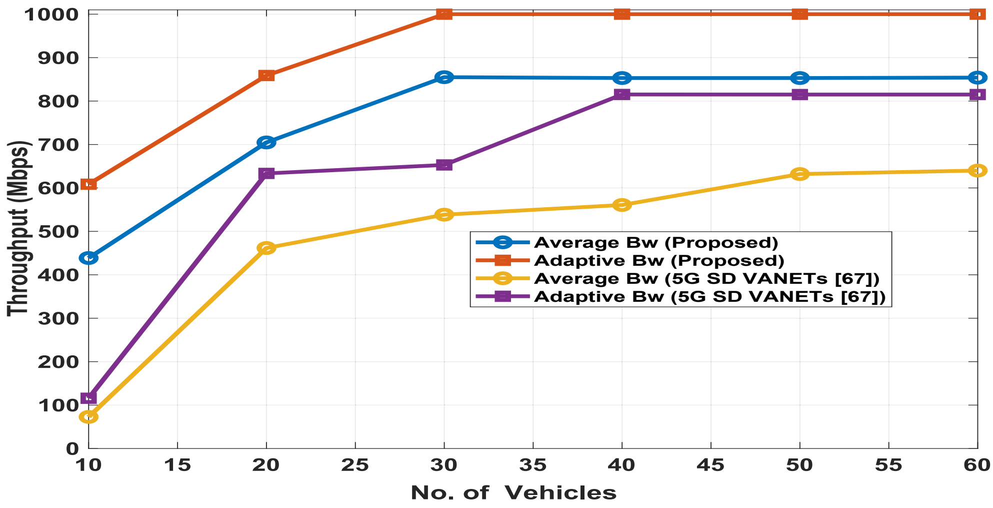


Figure 3.5: Comparison of Throughput using average and adaptive bandwidth allocation schemes

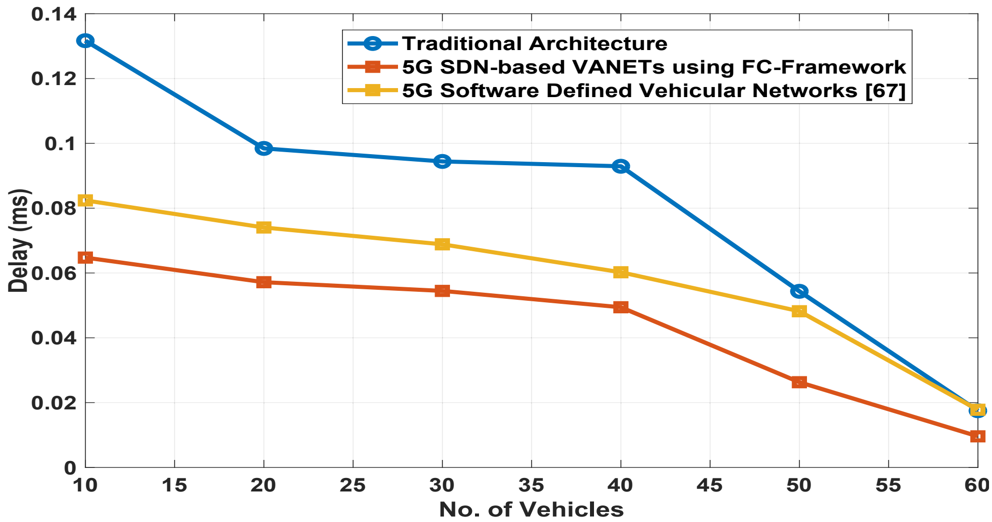


Figure 3.6: Delay Comparison

FC-framework.

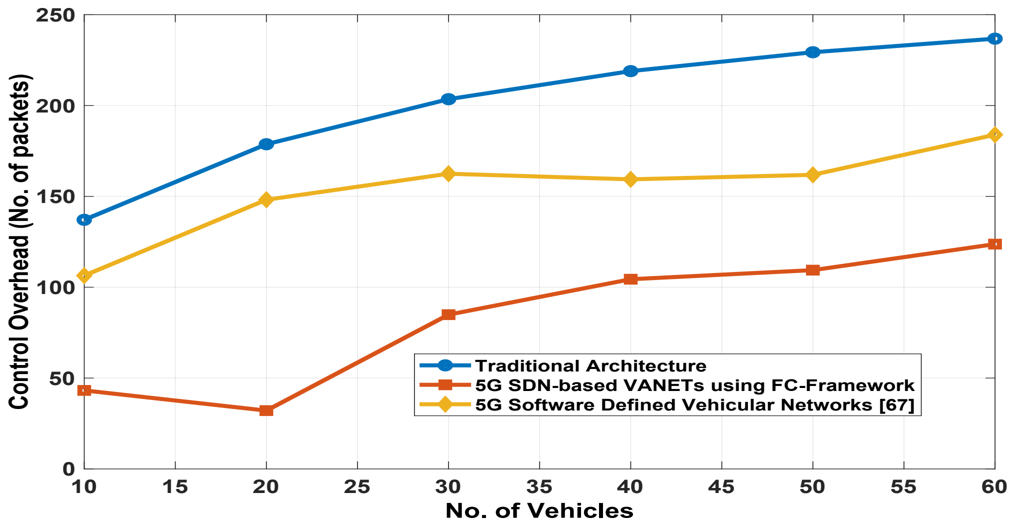


Figure 3.7: Comparison of Control overhead on controller

3.6 Conclusion

This chapter presents a new hierarchical 5G next generation VANET architecture, by employing the concepts of SDN, C-RAN and fog computing technologies. The topology and logical structure of architecture is also discussed in detail. Moreover, a detailed background and overview of 5G enabler technologies for VANETs including SDN, Cloud-RAN and fog Computing technologies is also presented. Furthermore, a new Fog Computing framework is presented that offers delay-sensitive, location-awareness and mobility-based real time services suitable for future ITS scenarios. Using SDN and C-RAN technologies, the proposed architecture provides flexibility, programmability and effective resource allocation using control plane and centralised global knowledge, thus leading towards significant reductions in operating cost of operators.

It is concluded from the simulation results that the proposed architecture can provide improved throughput, reduced transmission delay and minimized overhead on controllers.

Chapter 4

An Evolutionary Game Theoretic (EGT) Approach for Stable and Optimized Clustering in VANETs

4.1 Introduction

Discovering and maintaining efficient routes for data dissemination in Vehicular Ad hoc Networks (VANETs) has proven to be a very challenging problem. Clustering is one of the control protocols used to provide efficient and stable routes for data dissemination. However, the rapid changes in network topology in the VANETs creates frequent cluster reformation, which seriously affects route stability.

The main objective of this chapter is to present a novel Evolutionary Game Theoretic (EGT) framework to automate the clustering of nodes and nomination of cluster heads, to achieve the cluster stability in the VANETs.

The main contributions of this chapter can be summarized as follows;

- An EGT framework is presented for proposed FC Framework to solve the problem of cluster in-stability in VANETs. Using this approach, the clustering of nodes and nomination of cluster heads is automated in VANETs.

- Our proposed approach is lightweight and semi-distributed, and allows faster convergence. Our proposed approach reduces the signalling overhead and complexity, and increases cluster stability in large scale VANETs. In our proposed approach, significantly low ***signalling*** i.e., the average throughput of all clusters, is handled in a centralized manner, and the ***decision-making process*** (i.e., the automated adjustment and nomination of cluster heads) is performed in a ***decentralized evolutionary fashion***.

- The solution of the game is presented to be an evolutionary equilibrium. The equilibrium point is also proven analytically and the existence of evolutionary equilibrium is also verified using Lyapunov function.

- The proposed game is analysed with different number of clusters for different populations and cost functions. An optimal cost is suggested that defines an optimum clustering.

- We present two performance evaluation approaches to test and analyse the behaviour and performance of our proposed game. Our first approach is based on *static scenarios* and in our second approach, we use *Manhattan grid* as a mobility model to analyse the behaviour of our proposed game.

The rest of the chapter is organized as follows. In Section 4.2, the current VANET clustering schemes presented in literature are briefly reviewed and a summary of VANET clustering problems is presented. Moreover some background on evolutionary games is also discussed in this section. Section 4.3 presents the details of our proposed EGT framework. Section 4.4 presents system model, solution approach and analytical proofs regarding convergence and stability of evolutionary equilibrium. In section 4.5, simulation set-up scenarios, results and discussions are presented. Finally, the work is concluded.

4.2 Background and Related Work

Due to an ever increasing demand on transportation management and safety in Intelligent Transportation Systems (ITS), the need for an efficient data dissemination framework has grown to the point where it is clearly understood that many future ITS systems should be developed with a stable underlying data communication network. To this end, clustering plays a vital role to provide an efficient and steady state routing in VANETs [68], [69], [70], [71], [72]. Clustering has emerged as an important research topic in VANETs to organize and manage the network in a more efficient way. Clustering can help different applications by improving the reliability of the reported measurements. For example, several WSN applications require an aggregate value to be conveyed to the observer thus reducing communication overhead in the network, leading to significant savings in resources [73]. In this case, sensors collect data of specific regions by providing more accurate information about their local regions. Other applications include habitat monitoring applications [74], defence systems [75] and WSN routing [68]. Clustering vehicles into different groups offers many benefits such as: stabilizing the dynamic topology of VANETs, making an optimum utilization of network resources, improving the routing efficiency by providing hierarchical routing, providing fast convergence rates with minimum overhead and saving power consumption [70], [71], [76]. Clustering improves network scalability of large scale VANETs by limiting the number of globally propagating control messages. Moreover, stable clustering in VANETs makes the dynamic topology of VANETs appear less dynamic and hence the structure of the network becomes more manageable. Research has shown that routing on the top of clustering architectures is more scalable and stable as compared to flat routing [77], [70], [73], [71]. Clustering in VANETs creates a hierarchy within the network, which helps in reducing the routing overheads and contention during route discovery and data forwarding. Clustering in VANETs is also considered to be one of the control schemes used to organize/coordinate the media access and to support reliable and scalable multihop communications in VANETs [78]. Moreover, clustering in VANETs can assist in providing supports for Quality of Service (QoS) requirements for both delay tolerant (road and weather information) and delay intolerant (safety messages) applications [79]. It is also shown that clustering in VANETs can effectively reduce data congestion [80]. Several clustering schemes have proposed to improve routing performance in VANETs [68], [73], [71], [81]- [82]. However, very few works have been performed for investigating the stability of the clustering itself. Furthermore, many of the proposed clustering protocols are based on greedy algorithms, which do not often provide an optimal/network-wide solution. Hence, the highly dynamic intrinsic characteristics of VANETs seriously affects cluster stability and results in frequent cluster reformation and reorganization in [8]. We believe that clustering strategies should consider a whole-of-network approach when creating a hierarchy in the network. The benefit of such an approach is that the overall routing performance and stability of the network would be improved. One approach to achieve this is through the integration of game-theoretic strategies in clustering algorithms. In this chapter, an EGT framework is proposed to model the interactive decision making process between vehicular nodes in order to provide stable and optimized clustering in VANETs as shown in Figure 4.1.

The proposed work investigates the performance of proposed protocol by providing stable and optimized clustering. The payoff of the proposed game is determined by the net utility. The utility of head is computed from the difference between *total throughput* of the entire cluster and the cost function. Cost is defined as a function of cluster size. Shannon's capacity is used to calculate the throughput of each node in the cluster. The objective of the utility function is based on maximizing the utility function. Each member is attached to one of the cluster heads which provides the highest SNR to the member. This criterion applies to any propagation scenario. We use *cluster size* to implement the cost function. This cost function is implemented at different values of cluster size to achieve the objective of optimized clustering for our proposed game framework. Further details about the payoff and utility function are presented in section 3.1. In next section of this chapter, VANET clustering protocols are discussed.

4.2.1 VANET Clustering Protocols

The VANET clustering protocols generally vary in the selection of metric for the cluster formation [83]. The cluster formation (grouping of vehicles) is based on a *single metric* and a *multi metric* cluster formation criteria. As illustrated in [70], VANET clustering protocols are also categorized as *Centralized Clustering* and *Decentralized or V2V Clustering*. In centralized clustering, the cluster formation is achieved via Road side Units (RSUs) based on periodic message exchange between RSU and the vehicular nodes. In Decentralized Clustering or V2V Clustering protocols, the cluster head election and cluster formation is usually achieved via exchange of *Hello Messages* between vehicles.

An overview of VANET clustering protocols is provided as follows.

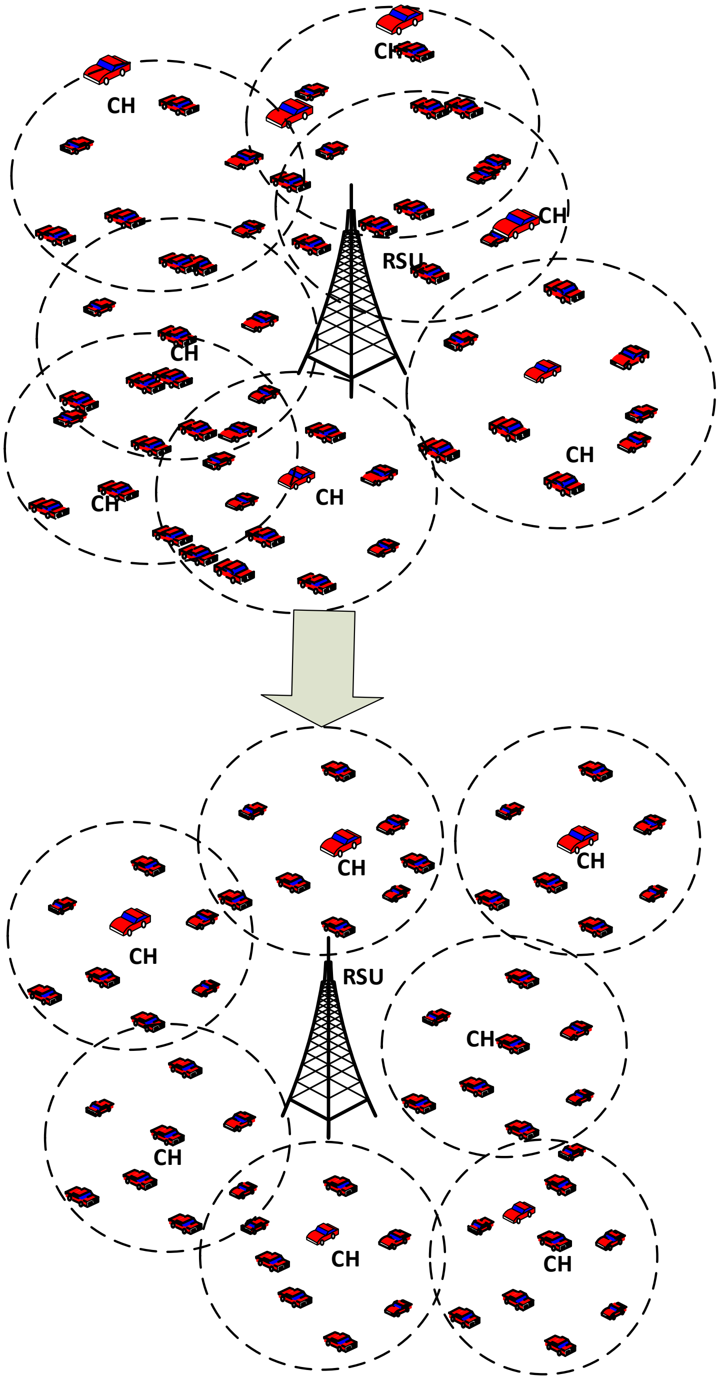


Figure 4.1: Proposed EGT Framework

1. ***Lowest ID Clustering:*** In [81], the cluster formation is done based on the lowest ID. The mobile nodes broadcast beacon messages in which node IDs are encapsulated. The node which has the lowest ID in its neighbourhood is selected as the cluster head node, while the other nodes are selected as cluster member nodes. This scheme does not take into account any of the dynamic characteristics of the network (e.g. node mobility, or node degree).

2. ***Mobility based clustering:*** The *MOBIC* [84] scheme uses a signal power level mobility metric to represent the relative mobility of nodes which are at one hop distance. An aggregate local mobility metric is the basis for cluster formation. When a mobile node receives two consecutive beacon messages from its neighbouring nodes, it measures the relative mobility between the two nodes as the ratio of the received signal strength of the new beacon message and the received signal strength of the old beacon message. The mobile nodes then calculate the aggregate mobility metric based on relative mobility. The mobile node having the least aggregate mobility is selected as a cluster head node. This scheme is most commonly used for comparison with other VANET clustering protocols. In [85], they propose a distributed mobility based data clustering algorithm. Affinity PROpagation for Vehicular networks (APROVE) that forms clusters with both minimum distance and minimum relative velocity between each cluster head and its members that helps to cluster nodes in a distributed manner by assuming vehicles know their positions using GPS. It is observed that APPROVE shows significant improvement in cluster stability, if compared with other scheme such as MOBIC. In [86], they propose two algorithms named as Distributed Clustering Algorithm (DCA) and Distributive and Mobility Adaptive Clustering DMAC. In these algorithms the nodes are grouped by following a new weight-based criterion that allows cluster head selection based on link quality and mobility-related parameters. The mobile nodes having the highest weight are selected as cluster head nodes. The DCA is used for clustering quasi static ad hoc networks, whereas DMAC algorithm adapts to the changes in the topology of network due to the mobility of nodes, therefore, more suitable for mobility based environments. In DCA, the weight is calculated thus having the possibility to express preferences on which nodes

are better suited to be cluster heads. In DMAC, each node reacts locally to any variation in the neighbouring topology, by changing its role (either cluster head or member node) accordingly. Moreover, It is also observed that the time complexity of the DCA is bounded by a network parameter that depends on the change in network topology rather than on the size of the network.

Another modified DMAC [87] is also proposed to improve the original DMAC. The goal of this algorithm is to improve cluster stability by avoiding re-clustering when two vehicles meet in different directions. The process of re-clustering is avoided if vehicles are moving in opposite directions. For the implementation of the modified features, each vehicular node needs to know its current location, velocity and moving direction as received from GPS or other location services. A new parameter called *freshness* is introduced for excessive re-clustering. The value of this parameter is calculated between two vehicular nodes by receiving hello messages and their movement direction data. The time to live (TTL) parameter helps in the construction of multi-hop clusters.

An Adaptive Mobility Aware Clustering Algorithm (AMACAD) is also proposed in [88] that aims to accurately follow the mobility patterns of vehicles in VANETs. This algorithm also tries to prolong cluster lifetime and reduce global overheads. The clustering metric considers the current location, speed and both relative and final destinations of vehicles.

Aggregate Local Mobility ALM [8] represents a new beacon based clustering approach that uses aggregate mobility as a clustering metric. This clustering protocol is aimed at prolonging the lifetime of a cluster in VANETs. The ALM weight is calculated similar to [84] except the difference that instead of using the Received Signal Strength RSS, which is highly unreliable, it uses location information of nodes using GPS or any other location services. A significant improvement in cluster lifetime and reduced node state/role changes is observed as compared to previous popular clustering algorithms. In [89] they proposed Density Based Clustering (DBC) to provide stable and long life clustering with a complex metric which takes into account the density of connection graph, traffic conditions and link quality for reliable communication.

3. ***Direction based clustering:*** A direction based clustering approach was proposed in [90] that is suitable for urban areas for VANETs. Vehicles are grouped into a clusters based on the prediction of directions of vehicles before intersections.

4. ***Multi-hop Clustering:*** Another multi-hop clustering scheme was presented in [91] that uses relative mobility as a metric between vehicles that are at multi-hop distance. In this scheme, a radio propagation delay based on beaconing is calculated at each node and is aggregated and propagated back to other vehicular nodes. The node with smallest aggregate mobility value is chosen as an appropriate cluster head. Moreover, cluster stability is increased by postponing the process of re-clustering for some interval of time when two cluster-heads come within the communication range of each other. The performance of the protocol is evaluated using different mobility models and by using 2, 3 and 5 hop clustering. Results show that cluster life time is prolonged using this scheme. In [92], the authors propose a clustering algorithm called as Vehicular Clustering based on weighted Clustering Algorithm (VWCA) based on a Weighted Clustering Algorithm technique (WCA). It consists of a complex metric calculated from vehicle movement direction and the number of neighbours that are based on dynamic transmission range. The VWCA technique is mainly aimed at improving the Cluster Head duration, membership duration and security. In [93] they propose an adaptive service provider infrastructure for VANETs (ASPIRE) that focuses on local network criticality and clustering in a distributed fashion. A fast randomized clustering and scheduling algorithm called as Hierarchical Clustering Algorithm (HCA) is presented in [94] that forms clusters in a hierarchical manner. HCA creates clusters within a diameter of at most four hops. HCA is robust in a sense that it does not rely on localization systems. In [95], a speed-overlapped clustering method is presented for highways that defines stable and unstable clustering neighbors depending on their speed and relative direction. A lane-based clustering algorithm is presented in [75] that is designed to provide stability in lifetime of clusters in urban scenarios. The process of cluster formation is based on selecting a cluster head from the lane where there will be a high

traffic flow. However, detecting the lane is a challenging task as each vehicle is assumed to know its exact lane by using a supplementary system such as, visual lane recognition, LIDAR etc. In [96] a new multi-metric cluster head election scheme has also been developed. The vehicles having similar mobility patterns, speed and travelling direction are grouped together within a cluster. This creates more stable clusters with increased cluster lifetime. The above presented clustering algorithms focus on different performance metrics and are optimized for different goals and objectives such as cluster stability, overhead minimization and fast cluster formation and etc. with the most predominant among them being cluster stability.

There is a need to put more research efforts to refine and optimize the cluster head election policy to present a stable clustering scheme. Moreover, there is a need to develop a clear definition of the generic terms of performance evaluation metrics (like cluster head stability, cluster head changes, average cluster stability and etc.) for clustering algorithms with respect to VANETs to provide consistency between different scientific studies [83]. Moreover, multi-hop and multi-homing capable clustering solutions require further research. In the next section, we discuss some motivations of using game theory as a solution approach for our proposed scheme.

4.2.2 Game Theory:

Game theory has emerged as a solution of various problems in the field of radio resource management, network formation, admission control, network selection and many others [97]. There are many games proposed in literature [98], but the game we propose to solve the problem of unstable clustering in VANETs has the theoretical grounds of EGT.

Our objective is to improve the throughput and stability of an entire network by adequately clustering nodes and nominating cluster heads. Bearing in mind the combinatorial nature of clustering and subsequently prohibitive complexity for centralized optimization, we propose to achieve the objective by formulating an evolutionary game theoretic framework. One reason for adopting the evolutionary game is due to the fact that each cluster forms a population, and the utility of the entire population is to be maximized. An evolutionary game is a population game, as opposed to many classical games, where each player selfishly maximizes its own gain. Another reason is, because each individual node has little rationality in a large network, such as VANETs, and the rationality of a node is based on instant knowledge of the responsive strategies that all other nodes take. Unfortunately, the knowledge grows with the network size and is impossible to acquire in practice. Replicator dynamics is adopted in our evolutionary game theoretic approach, to automate the nomination of cluster heads and refine the clusters, given little rationality at the nodes. With an increase in the number of nodes to large scales, replicator dynamics can help reduce overhead and complexity, and increase cluster stability. Specifically, the clusters with low throughput can replicate those with high throughput by encouraging cluster-edge nodes to switch between clusters. Within a cluster, a node maximizing the throughput of the cluster is nominated to be the cluster head. This continues until the network stabilizes, i.e., no cluster would enlarge or shrink and the cluster heads stop changing.

Note that cooperative games typically carried out in a centralized manner, have also been used to solve coalition formation problems and distribute the total gains to collaborative players in a fair fashion, such as the Shapley value method [98]. A cooperative game is typically suitable for small numbers of players, as it requires enumeration of possible coalitions and evaluation of their corresponding worths/payoffs to form coalitions. This is unsuitable for clustering in VANETs, where the network can be large and the number of possible coalitions is combinatorial to the network size. There are many games proposed in literature using EGT for solving different application in wireless networks. In [99], the authors presented an evolutionary game to model the problem of routing. There are other few approaches presented in heterogeneous wireless access networks that considered pricing or cost as a mechanism for resource allocation, admission control and network selection. Mainly three different approaches namely auction based [100], optimization based [101] and demand supply based [102] are applied to solve different problems in heterogeneous wireless access networks. Another approach is presented in [100] in which the mobile users used a bidding scheme for radio resource allocation from multiple radio access technologies by informing the service providers about the price and quality of service requirements. The service providers make resource allocation decisions in different wireless access networks to maximize the revenue. In short, cellular and broadband wireless access traditional systems such as 3G and WiMax or upcoming technologies like 5G or femtocell networks provoke a number of technical challenges arising from competitive and cooperative behaviour from wireless devices, making them potential candidates to be modelled using game theoretic tools [97].

4.3 Proposed EGT framework

In this section, an EGT framework is proposed to automate the clustering of nodes and nominations of cluster heads in VANETs. Initialized by a randomly generated clusters based on proximity, the proposed evolutionary game can achieve stable clusters and cluster heads, as shown in Fig. 4.1. Our proposed solution can also fine-tune the number of clusters between the games, until an adequate number of cluster heads are achieved with the highest total capacity. The stability of proposed EGT is also confirmed by Lyapunov stability analysis.

4.3.1 Proposed EGT Framework

The evolutionary game for clustering between vehicular nodes in VANETs is formulated as $G = \langle N, H, S, u_{C_h} \rangle$, where $N = \{1, 2, ..., n\}$ is the set of all vehicles and $H = \{1, 2, ..., j\}$ with $j \subset N$ is the set of randomly deployed clusters.

Utility function:

The net utility of a vehicular node i playing a strategy s_i from the strategy set $S = \{C_h, M\}$ is determined by its payoff, where C_h indicates the strategy the *cluster head* uses, and M indicates the strategy the*cluster member* uses. Depending on the total throughput of the entire cluster, the net utility of a clusterhead i is defined by

$$u_{C_{h\,i}} = c_1/n + \sum_{j=2}^{n} \frac{1/n}{\frac{1}{c\,j} + \frac{1}{c\,1}} - p_i(s_i) \tag{4.1}$$

where n is the number of nodes within the cluster, s_i is the current strategy of node i and $p_i(s_i) \geq 0$ is a cost function. Here, c_1 is the link capacity between the cluster head and the Road Side Unit (RSU), and c_j is the link capacity between a member

Components of proposed EGT framework	Components of VANETs
EGT Framework	An Evolutionary Game Theoretic (EGT) framework $G = \langle N, H, S, u_{C_h} \rangle$ as discussed in section 4.3.1.
Players	set of clusters $H = \{1, 2, ..., j\}$ with $j \subset N$ and $N = \{1, 2, ..., n\}$ is the set of all vehicles
Population	The population is assumed to be finite as represented by $N = \{1, 2, ..., n\}$
Utility function	The net utility of a vehicle is determined by its payoff that depends on total throughput of entire cluster and cost as mentioned in section 4.3.1
Objective of Utility function	The objective of a node playing C_h is to maximize utility u_{C_h} of cluster.

Table 4.1: Basic components of proposed EGT with respect to VANET clustering

Parameter	**Description**
$G = \langle N, H, S, u_{C_h} \rangle$	EGT game
N	Total number of vehicular nodes
$S = \{C_h, M\}$	Strategy set for vehicular nodes
s_i	Current strategy of node i
$N = \{1, 2, ..., n\}$	Set of vehicular nodes
$H = \{1, 2, ..., j\}$ with $j \subset N$	Set of clusters
u_{C_h}	net utility of a cluster head
$p_i(s_i)$	Cost function
T_{TC}	Total throughput of cluster
c_1	The link capacity between the cluster head and the Road Side Unit (RSU)
$c_j, j \subset N$	The link capacity between a member j within the cluster and the cluster head
d_H	The distance between the cluster head and the RSU
$d_{M,j}$	The distance between a member j from the cluster head

Table 4.2: List of parameters

j within the cluster and the cluster head. Consider prevailing contention-based random access techniques, namely, CSMA/CA, as standardized in IEEE 802.11p VANET. Transmission collisions need to be taken into the consideration of c_1 and c_j. Any pair of nodes with the received powers higher than the detection sensitivity (typically, around the noise floor) can suffer from transmission collisions. A pair of nodes can transmit concurrently with negligible interference, if the received power is lower and submerged in the noise. Exploiting Markov modelling techniques [103], the link capacity can be readily given by

$$\begin{aligned} c_1 =& \tau(1-\tau)^{N_h} \log_2(1+\phi(d_H)), \\ c_j =& \tau(1-\tau)^{N_h} \log_2(1+\phi(d_{M,j}) \end{aligned} \tag{4.2}$$

where N_h is the number of neighbors within sensitivity range of a node, d_H is the distance between the cluster head and the RSU, and $d_{M,j}$ is the distance between a member j from the cluster head. For analysis tractability, herein every node is assumed to have the same number of N_h neighbors within its sensitivity range. τ is the transmit probability of the node as per timeslot. Only depending on N_h, τ can be numerically evaluated a priori by solving [[103], eqs. 27 & 28]. We note that $\tau(1-\tau)^{N_h}$ is a common constant coefficient across all clusters, and does not affect clustering or the nomination of cluster heads. Therefore, it is suppressed in eq. 4.4 and onwards.

Objective of Utility function:

The objective of a node i playing a strategy C_h is to maximize the utility that is represented by the total throughput of cluster as represented by eq. (4.1). The expected utility of node acting as head is to evolve towards balanced network thus, achieving high throughput. This objective reflects the benefit gained by a vehicular node i to become a cluster head and the cost paid for resources for the cluster head.

Cluster Formation:

Each member node is associated with one of the cluster heads which provides the highest SNR to the member node.

Cost Function:

As discussed in utility function, the utility of cluster head is the difference between the reward of a selected strategy and the cost incurred by the cluster head from RSU. We use *cluster size* to implement the cost function. This cost function drives the clustering towards adequate sizes by keeping the cluster sizes and usage of capacity at an optimum.

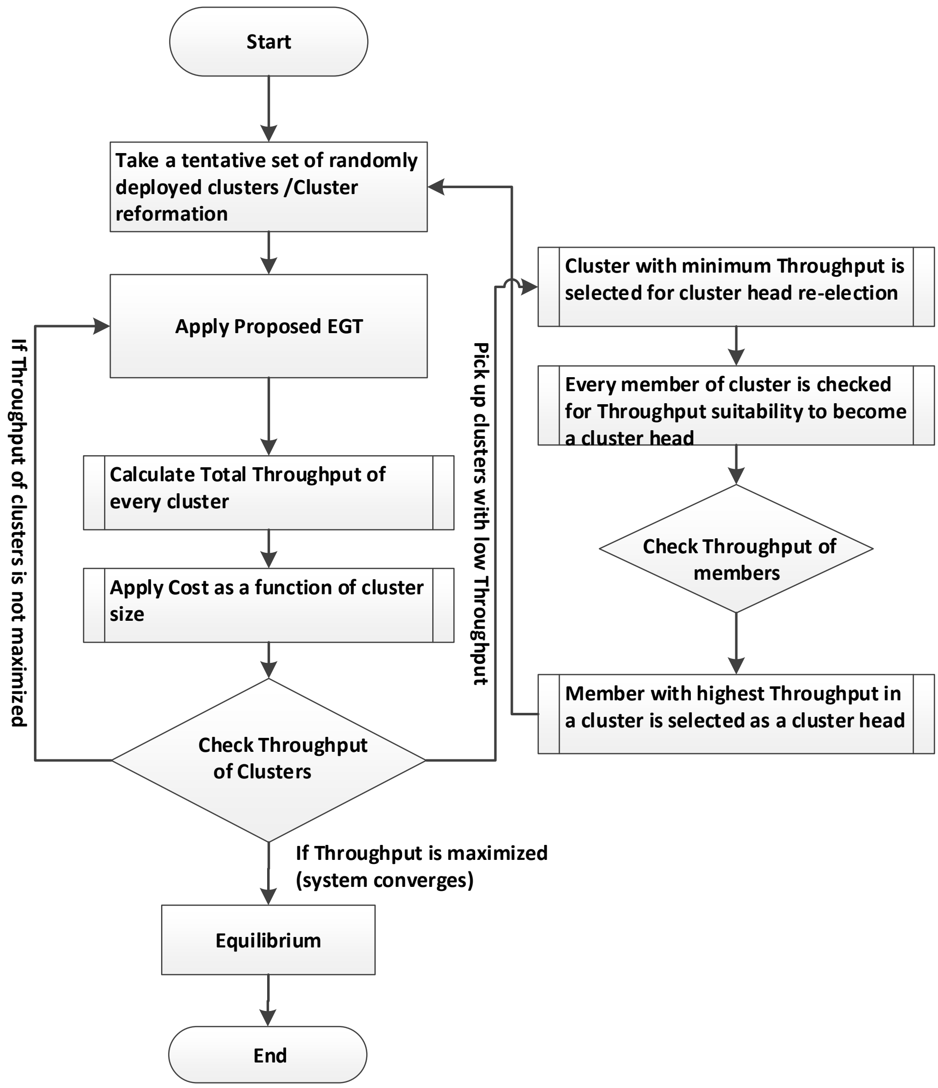


Figure 4.2: Flow Chart of Proposed EGT

4.4 System Model and Stability analysis

4.4.1 System Model

In this section, a detailed explanation of the proposed game framework is presented. List of used variables is also given in Tab. 4.2. A set of vehicles $N = \{1, 2, ..., n\}$ and clusters $H = \{1, 2, ..., j\}$ with $j \subset N$ are assumed to be deployed in a two dimensional grid of roads $\prod = [x_{min}, x_{max}] \times [y_{min}, y_{max}]$. We assume that the vehicles act as clients and RSU acts as the receiver. The vehicle play their strategies and make decisions, based on utility maximization of clusters, using a decentralized evolutionary fashion. We analyse the long term behaviour of the interactions of vehicular nodes in terms of automation of clustering of nodes and nomination of cluster heads in VANETs. The flow chart of our proposed EGT is presented in Fig. 4.2.

4.4.2 Solution Approach:

We deal with the problem of finding an evolutionary Nash equilibrium as a solution of our game. In a cluster, every node knows its neighbouring links and its own links towards RSU or sink, and this information is available for every node. In our proposed approach, the decision making process (i.e., the automation of adjustment of cluster-heads and nomination of cluster-heads) is performed in a ***decentralized evolutionary fashion***. For game theory, many games need to have centralized coordination like the one in coalition games. In proposed approach, ***centralized signalling*** is used to reduce the signalling overhead and to have an overall observation of the system. Furthermore, significantly low signalling is used on the overall throughput of the system. The RSU is broadcasting to all clusters to remove instability. A vehicular node gradually learns and adapts some decisions, until it reaches the point of evolutionary equilibrium that is a stable state with improved throughput. The vehicles adapt their strategies from a finite set of action profiles through payoff based strategy adjustment process [35]. In payoff based distributed learning, at any stage t, the vehicles know only their own actions and payoffs from $t-1$ previous stage and vehicles have no information about the actions taken by other vehicles. Therefore, at each time $t \geq 0$, each vehicle $i \in N$ selects an action profile $s_i \in S$ to maximize its expected utility. At every time step t, this game is repeated and after a sufficiently large number of repetitive stages, vehicles action profile reaches an evolutionary Nash equilibrium. It is important to note here that our proposed game is a non-cooperative game that is formulated based on the group behaviour of the vehicles for cluster formation and reorganization rather than depending upon the individual behaviour of nodes unlike other classical games. The payoff of the vehicle is the total net utility of a group of vehicles in a cluster [104]. Therefore, no vehicle has an incentive to deviate unilaterally at the point of evolutionary Nash equilibrium and at this state of the game, we achieve the objective of stable and optimized clustering in VANETs.

4.4.3 Replicator Dynamics and Stability of evolutionary equilibrium

In a dynamic evolutionary game, the strategy used by a vehicle from the population can be replicated by other vehicles through information received via centralized controller RSU. We use centralized signalling here to have an overall observation of the payoffs of all vehicles at RSU. The RSU calculates the average payoff of entire population of clusters and then broadcasts the information to all clusters. When the process of replication takes place over time, this can be modelled by a set of ordinary differential equations, called as *replicator dynamics* [98]. In our game, the replicator dynamics can be derived for population share of each cluster that is *cluster size*. In this scenario, a replicator with a higher payoff will replicate itself faster. The replicator dynamic equation for analysing the size of cluster is given as

$$\dot{p}_{H_i}(t) = \gamma p_{H_i}(t)[u_{C_{h_i}}(t) - \bar{U}(t)] \tag{4.3}$$

where γ is used to control the speed of convergence of strategy adaptation and $\gamma > 0$. $p_{H_i}(t) = n_i/N$ denotes the proportion of vehicles choosing cluster H_i and is also referred to as population share or the size of cluster. The population share of clusters can be denoted by the vector $p_H = [p_{H_1}, p_{H_2}, ..., p_{H_i}, ..., p_{H_m}]$. $u_{C_{h_i}}(t)$ is the payoff to become a cluster head. $\bar{U}(t)$ represents the average payoff of the entire population of clusters. The evolutionary equilibrium is defined as a set of fixed points of replicator dynamics that are stable. These fixed points are obtained

$$\frac{\partial p_{h_1}(t)}{\partial t} = \gamma \frac{n_1(t)}{N}\left[\left\{\frac{log_2(1+\phi(d_H(t))}{n_1(t)} + \sum_{j=2}^{n_1(t)} \frac{\frac{1}{n_1(t)}}{\sum_{k\epsilon\{H,(M,j)\}} \frac{1}{log_2(1+\phi_k(t))}} - p_1(t)\right\}\right.$$
$$\left. - \left\{\frac{log_2(1+\phi(d_H(t))}{n_2(t)} + \sum_{j=2}^{n_2(t)} \frac{\frac{1}{n_2(t)}}{\sum_{k\epsilon\{H,(M,j)\}} \frac{1}{log_2(1+\phi_k(t))}} - p_2(t)\right\}\right] \tag{4.5}$$

numerically and at these fixed points the rate of strategy adaptation γ is zero or the first order derivative of the proportion of vehicles choosing cluster H_i is $\dot{p_{H_i}} = 0$. None of the vehicles will change their strategy at these fixed points, since their payoff is equal to the average payoff of the entire population of vehicles. The evolutionary equilibrium of our proposed evolutionary game exists, while the equilibrium might not be unique. Any initial random clustering leads to a stable clustering result, although the stable clustering can be different due to different initial clustering. The existence of an evolutionary equilibrium is of paramount importance to VANETs and can be verified by using Lyapunov Stability analysis. *Lyapunov function* can be used to evaluate the willingness of a node to deviate from a fixed point. To evaluate the stability of fixed point say $pH_i{}^*$, obtained by $\dot{p_{H_i}} = 0$, the eigenvalue values of the Jacobian matrix that corresponds to the replicator dynamics need to be evaluated. If all eigenvalues have a negative part, the fixed point is stable [105].
To simplify the problem we first investigate the stability of evolutionary equilibrium for two clusters that is $H = 2$ (as often considered in [106] and [107]). We first show that the average total throughput capacity T_{TC} of a given cluster declines monotonically with the increasing size of clusters. Now eq. 4.3 can be rewritten as

$$\frac{\partial p_{h_i}(t)}{\partial t} = \gamma \frac{n_i}{N}\left[\left(\frac{c_i}{n_i} + \sum_{j=2}^{n_i} \frac{\frac{1}{n_i}}{\frac{1}{c_j}+\frac{1}{c_i}} - p_i\right) - \right.$$
$$\left. \sum_k \left(\frac{c_k}{n_k}\sum_{j=2}^{n_k} \frac{\frac{1}{n_k}}{\frac{1}{c_j}+\frac{1}{c_k}} - p_k\right)\right] \tag{4.4}$$

For analysing the stability of two clusters eq. 4.4 can be rewritten in the form of eq. 4.5 and eq. 4.6. For $H = 2$, to find the equilibrium point for $n1$ and $n2$, the

$$\frac{\partial p_{h_2}(t)}{\partial t} = \gamma\frac{n_2(t)}{N}\Bigg[\left\{\frac{log_2(1+\phi(d_H(t))}{n_2(t)} + \sum_{j=2}^{n_2(t)} \frac{\frac{1}{n_2(t)}}{\sum_{k\epsilon\{H,(M,j)\}}\frac{1}{log_2(1+\phi_k(t))}} - p_2(t)\right\}$$
$$- \left\{\frac{log_2(1+\phi(d_H(t))}{n_1(t)} + \sum_{j=2}^{n_1(t)} \frac{\frac{1}{n_1(t)}}{\sum_{k\epsilon\{H,(M,j)\}}\frac{1}{log_2(1+\phi_k(t))}} - p_1(t)\right\}\Bigg] \quad (4.6)$$

above equations can be rewritten as

$$\begin{aligned}\frac{\partial p_{h_1}(t)}{\partial t} &= \gamma\frac{n_1}{N}f_1(n1) = 0 \\ \frac{\partial p_{h_2}(t)}{\partial t} &= \gamma\frac{n_2}{N}f_2(n2) = 0\end{aligned} \quad (4.7)$$

We are able to find the equation for equilibrium point, since $f_i(n_i)$ is monotonic with respect to n_i. Since $n_1 = 1 - n_1$, we can calculate the equilibrium point n_e by solving

$$\frac{f_1(n_1)}{n_1} = \frac{f_2(1-n_1)}{1-n_1} \quad (4.8)$$

The equilibrium point n_e exists, since $\frac{f_1(n_1)}{n_1}$ and $\frac{f_2(n_2)}{n_2}$ are monotonic. Fig. 4.3 gives an illustration of how we get the equilibrium point. The equation for equilibrium point n_e is given as

$$n_e = n_1 = \frac{f_1(n_1)}{f_1(n_1) + f_2(1-n_1)} \quad (4.9)$$

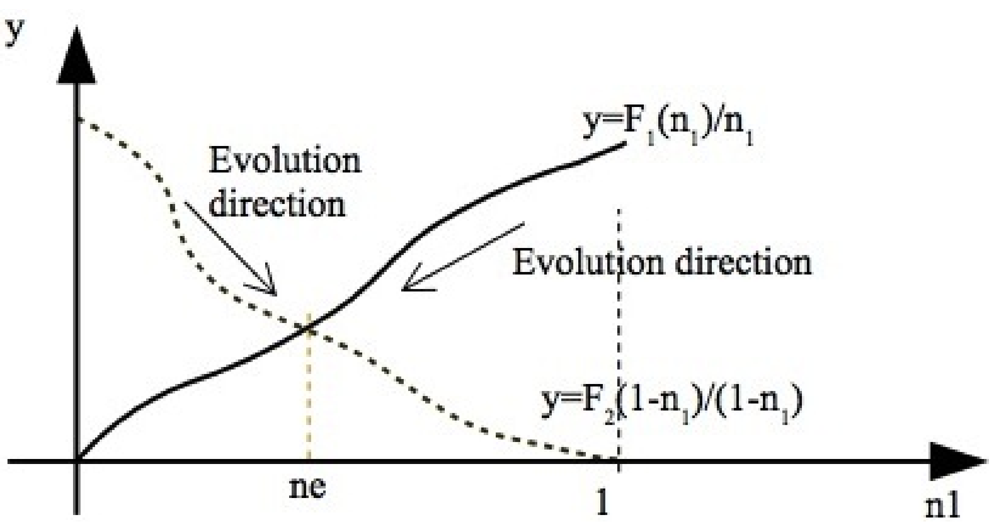


Figure 4.3: An illustraion of equilibirum point n_e

For our case, we define a candidate Lyapunov function as $V(n_i) = \frac{1}{2}(n_i - n_e)^2$ such that value of $V(n_i) \geq 0$ around the equilibrium point n_e of the system. To check the first order derivative of $V(n_i)$ along the trajectories of system with respect to time t, the equation is given by

$$\frac{\partial V(n_i)}{\partial t} = \frac{\partial V(n_i)}{\partial n_i}\frac{\partial n_i}{\partial t} \tag{4.10}$$

Hence, we get the result as

$$\frac{\partial V(n_i)}{\partial t} = (n_i - n_e)\,\gamma n_i\,(\mathrm{T_{TC}i(n_i)} - \mathrm{T_{TC}i'(1 - n_i)}) \tag{4.11}$$

where $T_{TC}i$ is the payoff of cluster i and $T_{TC}i'$ is the average payoff of all other clusters in the network. Fig. 4.4 shows the equilibrium point for the system. It

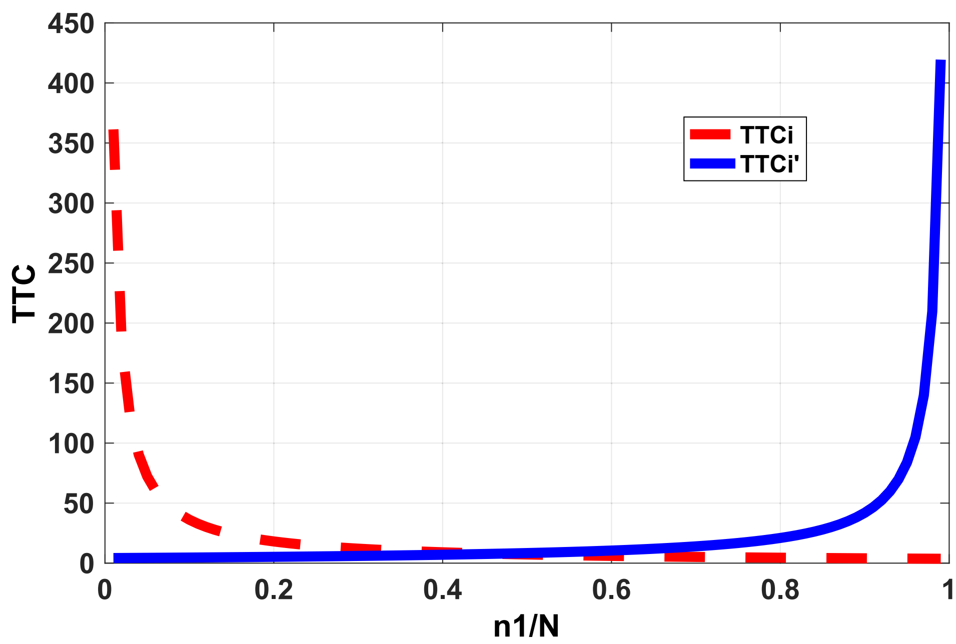


Figure 4.4: Equilibrium point for Population share n_i/N

is observed that $\frac{\partial V(n_i)}{\partial t} \leq 0$ for any $0 \leq n_i \leq 1$. It is clearly shown from Fig. 4.4 that as n_i/N grows, the factor $(T_{TC}i(n_i) - T_{TC}i((n_i)'))$ and $(n_i - n_e)$ will always take opposite signs. The equality holds if and only if $n_i = n_e$ as shown in Fig. 4.3 and Fig. 4.4. This conclusion may be generalized for $H \geq 2$ for which Fig. 4.4 will become multidimensional. For example, for $H = 3$, the condition of $\frac{\partial V(n_i)}{\partial t} \leq 0$ for all $0 \leq n_i \leq 1$ will still hold and the curves will be replaced by planes with a point intersecting at equilibrium point n_e. It is worth mentioning that the equilibrium point n_e would be different for different initial deployment and mobility of nodes in clusters. Since the value of $f_i(n_i)$ depends on node positions and their mobility. Therefore, a generalized expression for $f_i(n_i)$ cannot be derived. Our above analysis confirms that our proposed game is stable under any initial random deployment of clusters and this is due to the monotonicity of average payoff T_{TC} of clusters as shown in Fig. 4.4. To check the stability of equilibrium, point and to find the

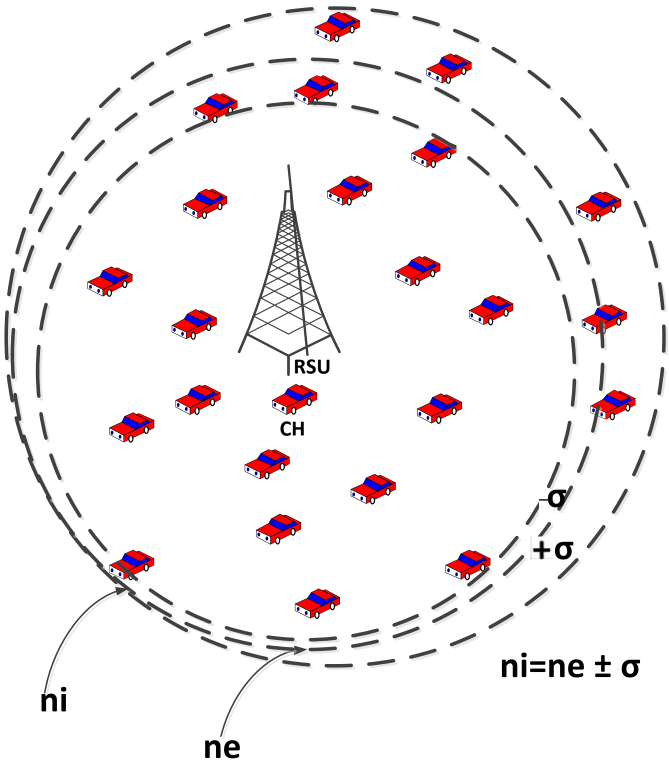


Figure 4.5: Boundary of equilibrium in the region of $n_i = n_e \pm \delta$ for all $0 \leq n_i \leq 1$ where $\delta \ll 1$

boundary conditions for the equilibrium point, we check the value of $\dot{V}(n_i)$ in the region of $n_i = n_e \pm \delta$ where $\delta \ll 1$ as shown in Fig. 4.5. Our analysis confirms that by applying $n_i = n_e \pm \delta$ to eq. 4.11 where $\delta \ll 1$, the condition $\dot{V}(n_i) \leq 0$ still holds, when number of nodes is finite and n_e is not an integer. By using $\mathrm{T}_{TC}1$ and $T_{TC}2$ as

$$T_{TC}1 = \frac{1}{n_1(t)} \left\{ log_2(1 + \phi(d_H(t)) + \sum_{j=2}^{n_1(t)} \frac{1}{\sum_{k\epsilon\{H,(M,j)\}} \frac{1}{log_2(1+\phi_k(t))}} - n_1(t)p_1(t) \right\}$$

$$T_{TC}2 = \frac{1}{n_2(t)}\left\{log_2(1+\phi(d_H(t)) + \sum_{j=2}^{n_2(t)} \frac{1}{\frac{1}{\sum_{k\epsilon\{H,(M,j)\}}\frac{1}{log_2(1+\phi_k(t))}}} - n_2(t)p_2(t)\right\}$$

Reforming above expressions in terms of $\frac{n_i}{N}$ and $\frac{1-n_i}{N}$ we get

$$T_{TC}1 = \frac{1}{n_1(t)N}\left\{log_2(1+\phi(d_H(t)) + \sum_{j=2}^{n_1(t)N} \frac{1}{\frac{1}{\sum_{k\epsilon\{H,(M,j)\}}\frac{1}{log_2(1+\phi_k(t))}}} - n_1(t)Np_1(t)\right\}$$

$$T_{TC}2 = \frac{1}{1-n_1(t)}\left\{log_2(1+\phi(d_H(t)) + \sum_{j=2}^{1-n_1(t)} \frac{1}{\frac{1}{\sum_{k\epsilon\{H,(M,j)\}}\frac{1}{log_2(1+\phi_k(t))}}} - (1-n_1)(t)Np_2(t)\right\}$$

Further assuming

$$T_{TC}1 = \frac{1}{n_1(t)N}\left\{Temp1 - n_1(t)Np_1(t)\right\}$$

$$T_{TC}2 = \frac{1}{1-n_1(t)}\left\{Temp2 - (1-n_1)(t)Np_2(t)\right\}$$

Hence eq. 4.11 becomes

$$\frac{\partial V(n_1)}{\partial t} = \frac{\pm\delta\gamma n_1}{N}\left(Temp1 - n_1(t)Np_1(t)\right) - \frac{\pm\delta\gamma n_1}{(1-n_1)N}\left(Temp2(1-n_1)(t)Np_2(t)\right)$$

Applying $n_1 = n_e \pm \delta$.

$$\frac{\partial V(n_1)}{\partial t} = \frac{\pm\delta\gamma}{N}\left\{Temp1 - Temp2\left(\frac{n_e \pm \delta}{1-n_e\pm\delta}\right) - (n_e\pm\delta)\,N\,(p_1(t)-p_2(t))\right\} \tag{4.12}$$

It is clear from eq. 4.12 that $\frac{\partial V(n_1)}{\partial t}$ will be zero if $\delta = 0$. At equilibrium point $Temp1 = Temp2\left(\frac{n_e}{1-n_e}\right)$,hence eq. 4.12 becomes

$$\frac{\partial V(n_1)}{\partial t} = \frac{\pm\delta\gamma}{N}\left(Temp2\left\{\left(\frac{n_e}{1-n_e}\right) - \left(\frac{n_e\pm\delta}{1-n_e\pm\delta}\right)\right\}\right) \tag{4.13}$$

From eq. 4.13 if we take positive sign of δ, applying $n_1 = n_e + \delta$

$$\frac{\partial V(n_1)}{\partial t} = \frac{+\delta\gamma}{N}\left(Temp2\left\{\left(\frac{n_e}{1-n_e}\right) - \left(\frac{n_e+\delta}{1-n_e-\delta}\right)\right\}\right)$$

The equation yields a negative result since the factor $\left\{\left(\frac{n_e}{1-n_e}\right) - \left(\frac{n_e+\delta}{1-n_e-\delta}\right)\right\}$ is less than zero. In the same way if we take negative sign of δ, applying $n_1 = n_e - \delta$ eq. 4.13 becomes

$$\frac{\partial V(n_1)}{\partial t} = \frac{-\delta\gamma}{N}\left(Temp2\left\{\left(\frac{n_e}{1-n_e}\right) - \left(\frac{n_e-\delta}{1-n_e+\delta}\right)\right\}\right)$$

The equation yields positive result since $-\delta < 0$. Hence the above mathematical analysis confirms the stability of our proposed clustering game. Due to the discrete nature of cluster size in VANETs a ping-pong effect is observed within a small local area of equilibrium point that is usually common to evolutionary games [106] and [105]. Results show that this ping-pong effect remains within a small neighbourhood of equilibrium point n_e and will never deviate from this area as shown in Fig. 4.6. Hence our results strengthen the stability of evolutionary equilibrium of our proposed

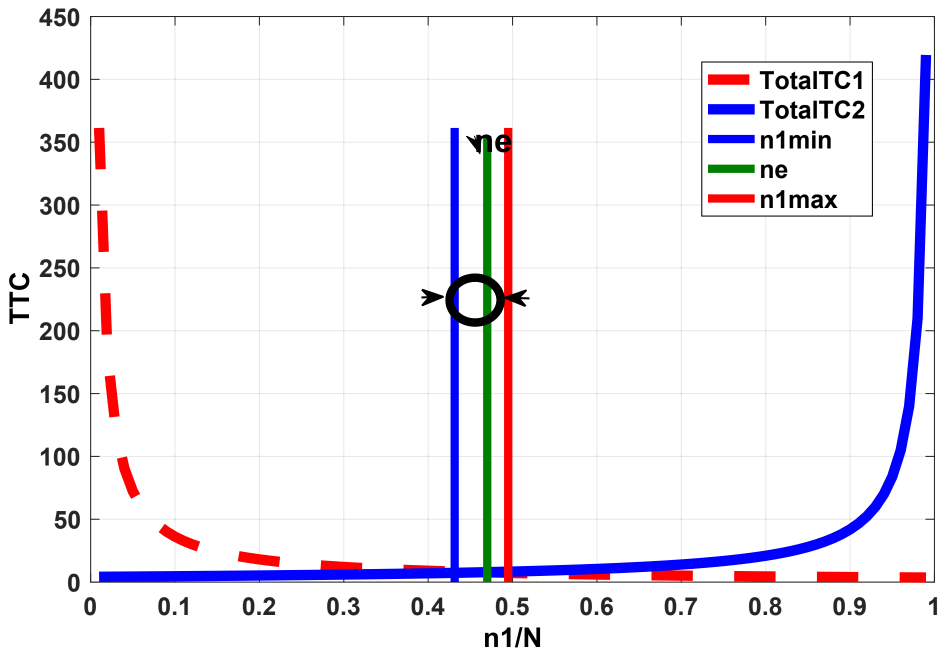


Figure 4.6: Stability of equilibrium point for n_1/N within $n_1 = n_e \pm \delta$

game.

4.4.4 Complexity Analysis

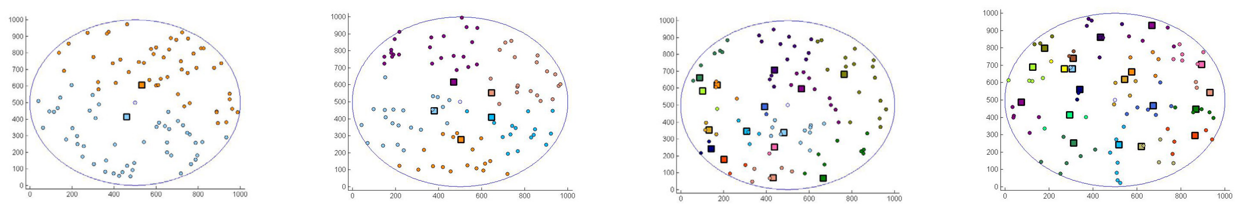
To analyse the complexity of our proposed protocol, we consider a graph $G := (N, H)$ comprising a set N of vertices together with a set $H \subset N \times N$ of edges. There are a total of H^N possible configurations of signalling. We analyse the number of control packets exchanged between RSU and cluster-heads. Let the average number of *head-RSU* control packets be represented by S. Then the total number of subsets of S is given by 2^S. Equating the total possible configurations of signalling to the total number of subsets of S, we get

$$2^S = H^N$$
$$S \approx N \log_2(H) \tag{4.14}$$

Hence, the complexity of control overhead for *head-RSU* signalling is $\mathcal{O}(N \log_2 H)$ with respect to the number of nodes (N) and number of heads (H) which is also supported by the result of the simulation in Fig. 4.17.

4.5 Simulation set up scenarios and results

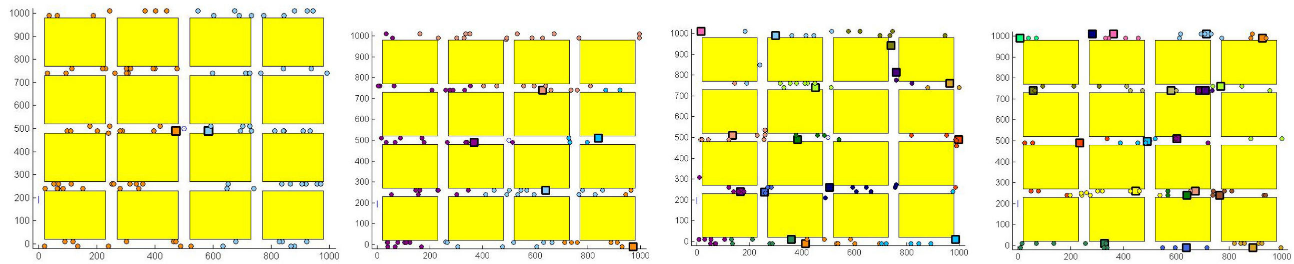
We present two approaches to analyse the performance of our proposed game. Performance evaluations for both *static* and *mobility* based scenarios are made via simulations using MATLAB as shown by running simulations in Figs. 4.7 and 4.8. The wireless standard used for simulation is IEEE 802.11p. The mobility model we chose to run the set of experiments is the *Manhattan grid* model. This model offers



(a) EGT simulation with 2 clusters (b) EGT simulation with 5 clusters (c) EGT simulation with 15 clusters (d) EGT simulation with 20 clusters

Figure 4.7: Simulation snapshots using Static Scenarios

more realistic mobility patterns on streets and in urban areas. The geographical area of VANET is partitioned into two dimensional bidirectional grids (assuming two way roads). The grid of roads is placed after every $250m$. Initially all the vehicles are deployed randomly in an area of $1000X1000m$. After a node begins to move and reaches at the next intersection, the direction of vehicular node is decided probabilistically. A node has 50% chance of continuing in the same direction and



(a) EGT running simulation with 2 clusters (b) EGT running simulation with 5 clusters (c) EGT running simulation with 15 clusters (d) EGT running simulation with 20 clusters

Figure 4.8: Simulation snapshots using Manhattan Grid Mobility

25% chance of turning to the west/South directions and an equal 25% chance of turning to east/north direction. Vehicles are assumed to be randomly deployed in the network. All vehicles act as clients and the RSU acts as a receiver. The details of network simulation parameters are given below in Tab. 4.3. We first take a tentative set of randomly deployed cluster-heads in the network. All vehicles start at the same time and the vehicles within the range of RSU establish connection with the RSU. In the same way, each member joins one of the cluster heads which provides the highest SNR to the member. We apply our proposed EGT approach based on utility maximization by using eq. (4.1). We assumed cost p as a function of cluster size and we analysed results on different values of cost function. We initially assume different numbers of clusters, that is $2, 5, 10, 15, 20$ and apply our proposed EGT game to investigate the performance of clustering for both static and mobility based scenarios.

The trajectory of evolutionary equilibrium in figures 4.9 and 4.10 shows that the system converges to a certain point where the stability of clusters is retained and the clusters evolve towards balanced sizes with converged average total throughput. Moreover, at the point of evolutionary equilibrium, there is no more role switching between vehicles (i.e., from cluster head to member or member to cluster head) takes place. In the same way, we tested the system with different inputs of clusters as $25, 30, 35, 40...$ We investigate the point where the average total throughput is maximized both for static and mobile scenarios as shown in Fig. 4.13 and Fig.4.14. This is the point where we achieved the optimum number of clusters for our proposed scenario as the throughput is maximized at this point. It is also observed that we

Parameter	**Static Scenarios**	**Mobility**
Length of Road	$1000m$	$1000m$
Number of Vehicles	100	100
Position of RSU	$x = 500, y = 500$	$x = 500, y = 500$
Transmission range of RSU	$500m$	$500m$
Mobility Model	Random and Static	Manhattan Grid Mobility
PHY and MAC layer protocol	IEEE 802.11p	IEEE 802.11p
Normalized Transmit power PTx	$20mW$	$20mW$
$Rx_{noise}(-90dBm)$	$1e-9mW$	$1e-9mW$
Wavelength λ	$0.125m$	$0.125m$
Average Speed of vehicles	$0m/Sec$	$20m/sec$, $30m/sec$, $45m/sec$, $65m/sec$
Simulation interval	$.01sec$	$.01sec$

Table 4.3: Network configuration parameters in static scenarios and mobility using Manhattan grid

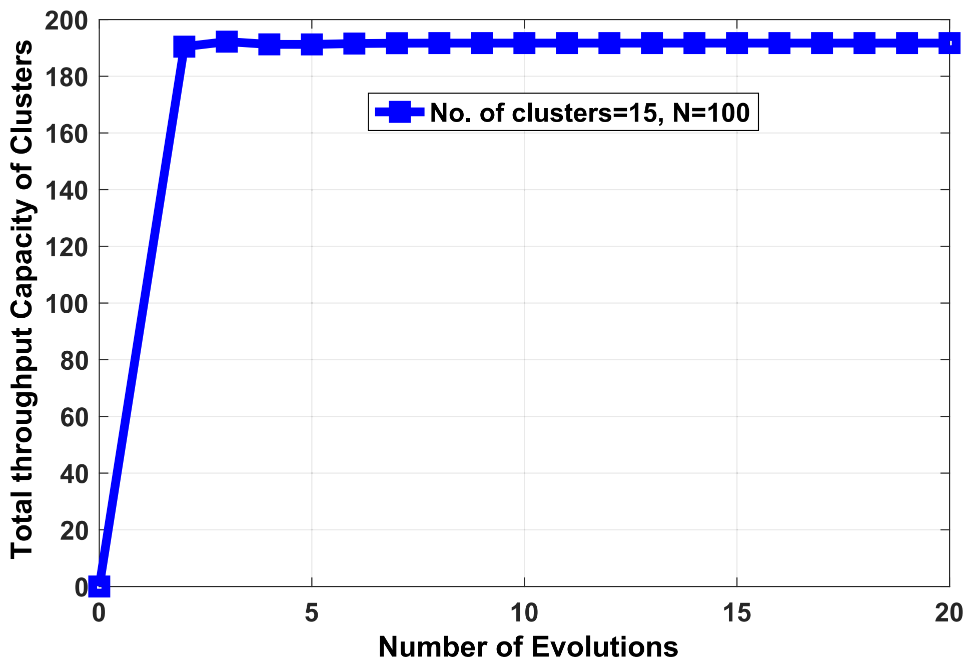


Figure 4.9: Stability convegence of System with 15 clusters in static scenario

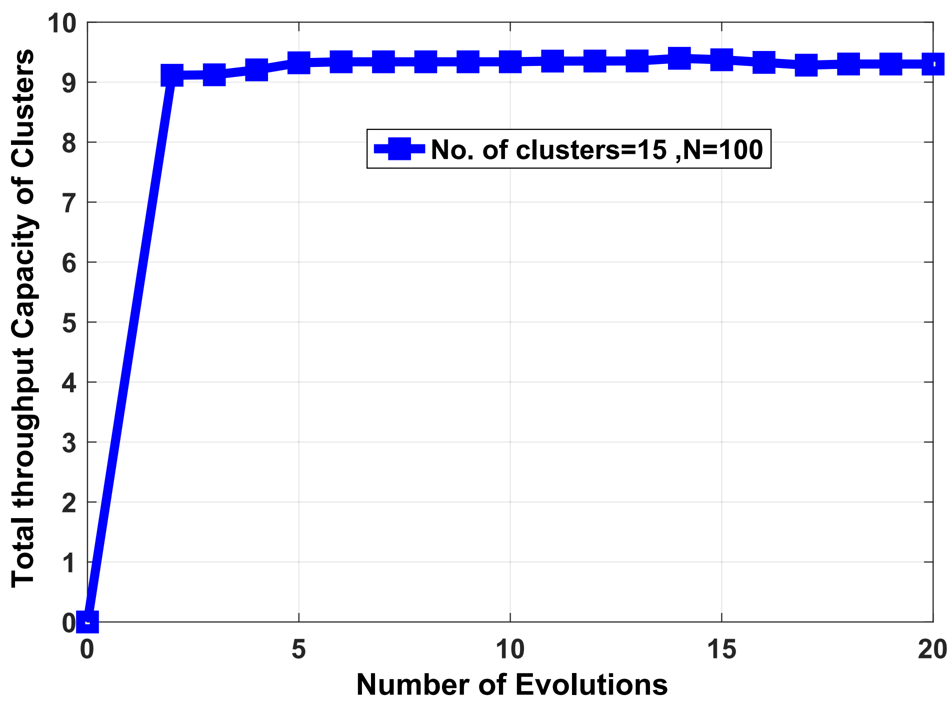


Figure 4.10: Stability convergence of System with 15 clusters using Manhattan grid mobility

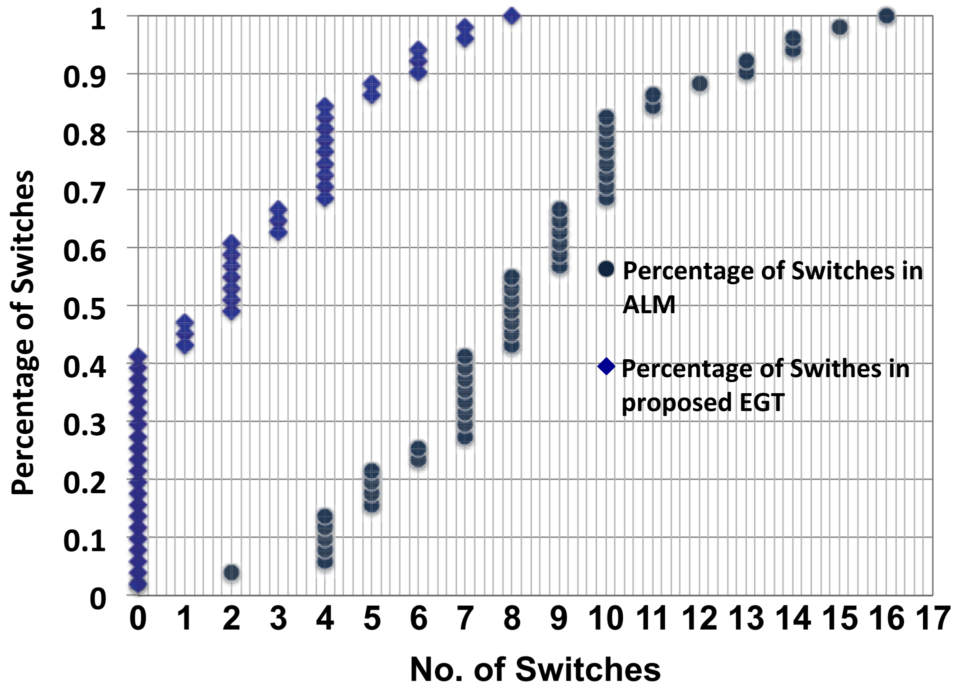


Figure 4.11: Comparison of Switching rate of Proposed EGT with ALM [8]

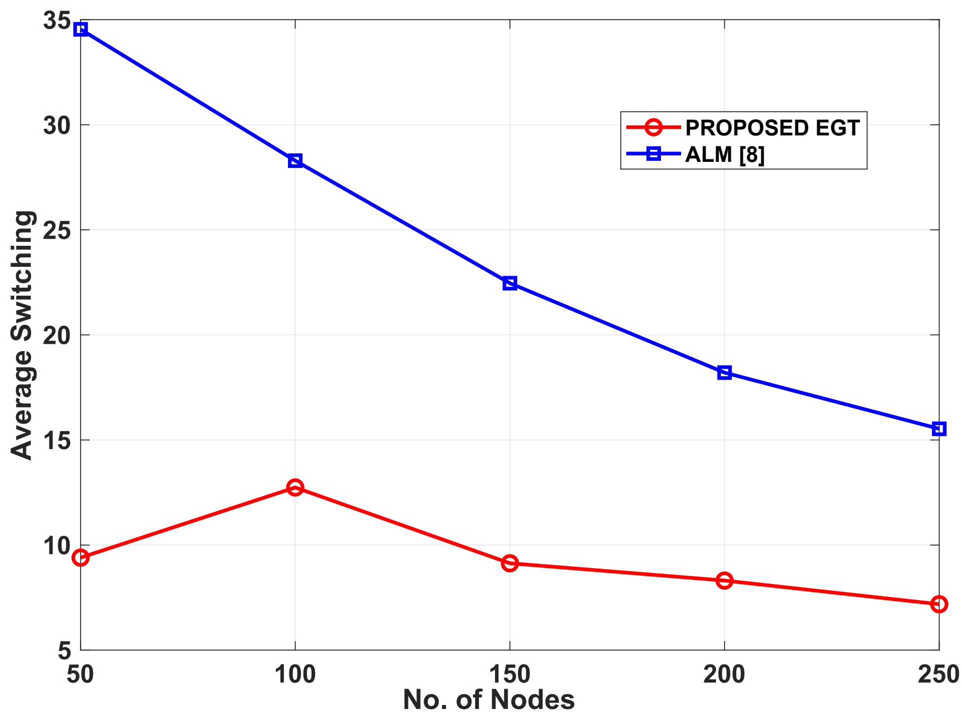


Figure 4.12: Comparison of Average switching rate of proposed EGT with ALM [8]

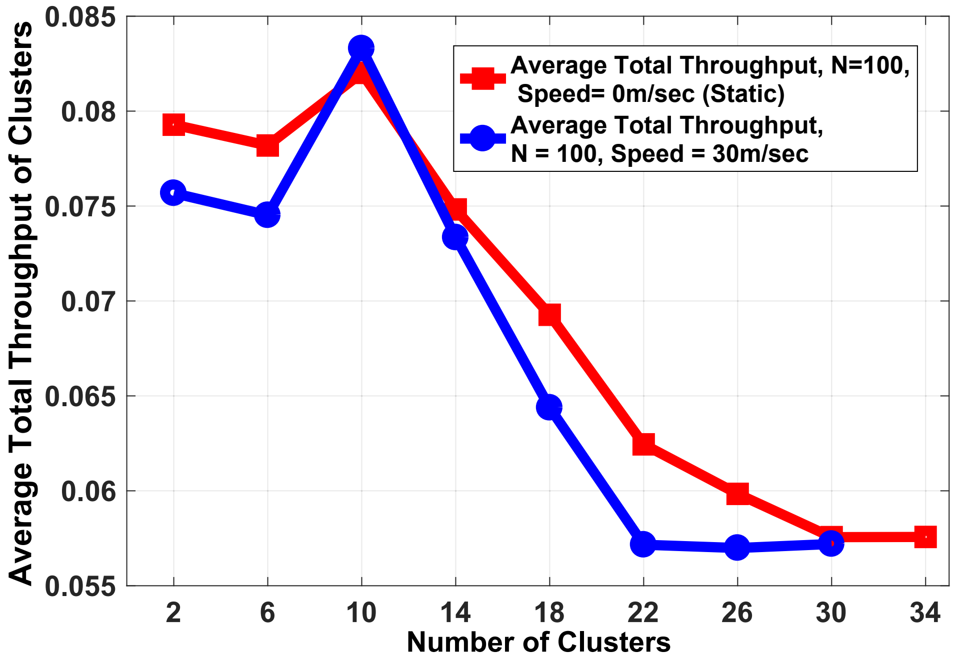


Figure 4.13: Throughput maximization for static scenario and Manhattan grid

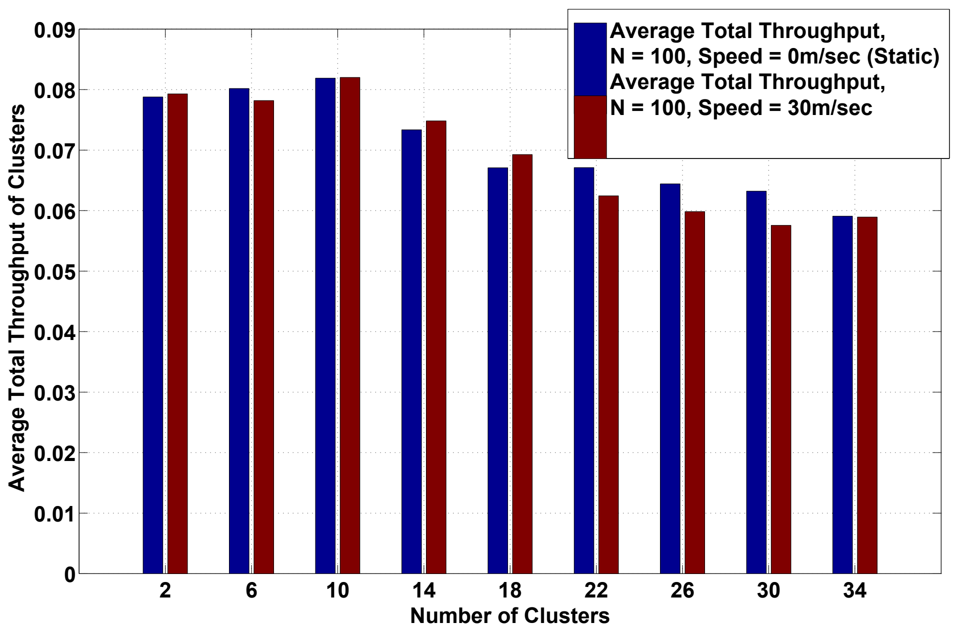


Figure 4.14: Optimum no. of clusters for static scenario and Manhattan grid

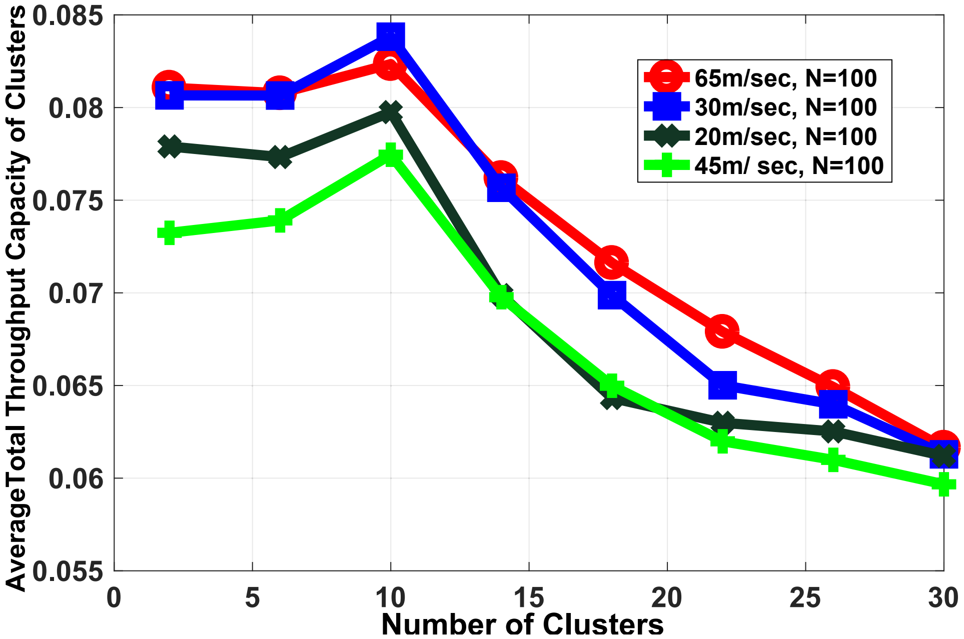


Figure 4.15: Comparison of Throughput maximization at different speeds for N=100

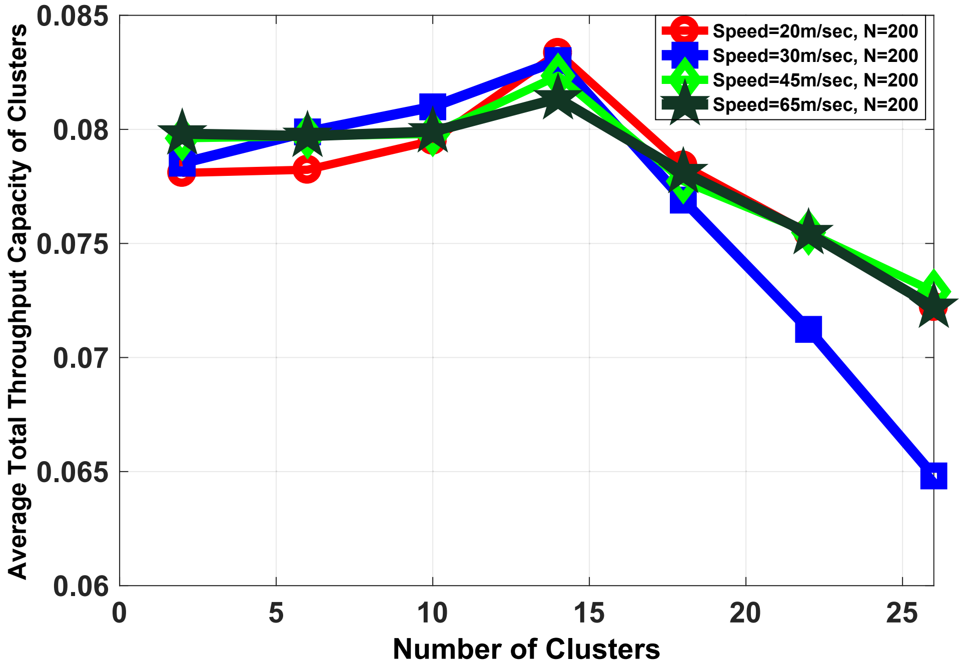


Figure 4.16: Comparison of Throughput maximization at different speeds for N=200

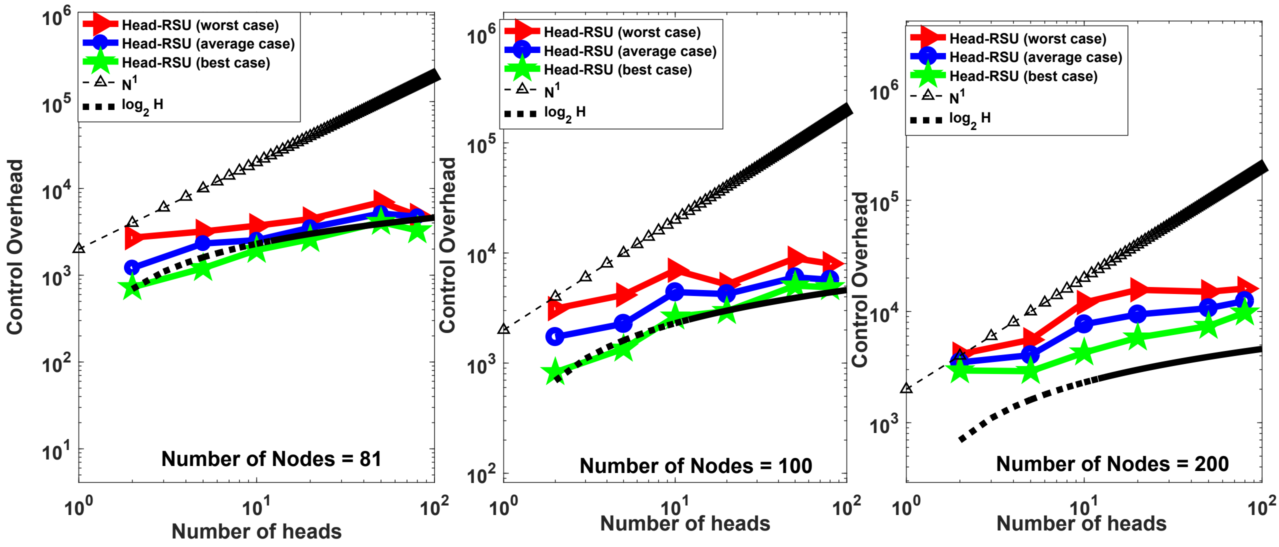


Figure 4.17: Complexity Analysis

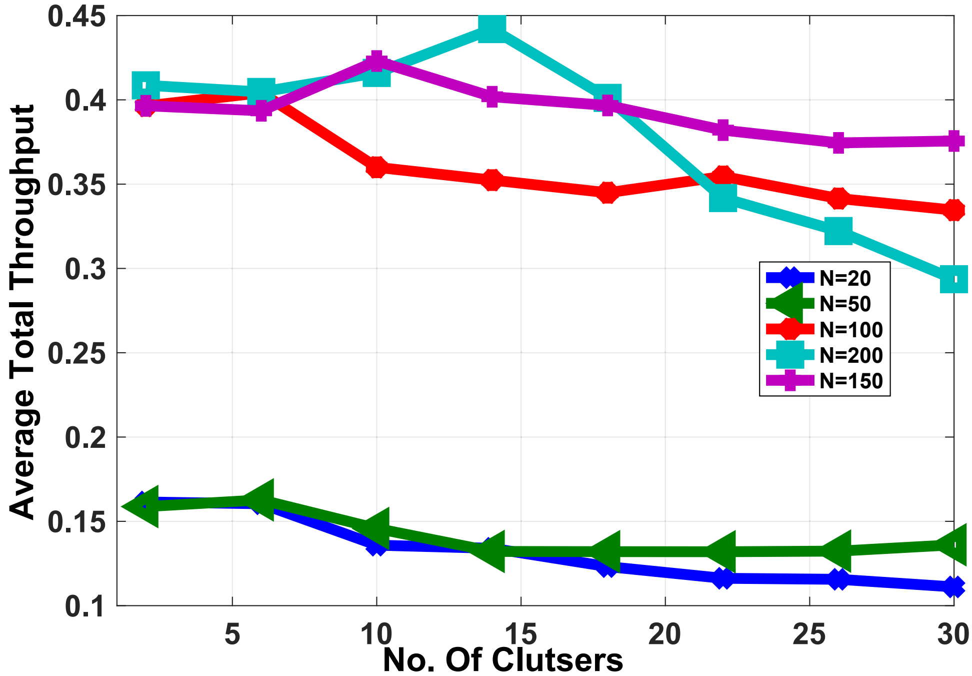


Figure 4.18: Scalibility anaylysis for thorughput maximization at different population sizes

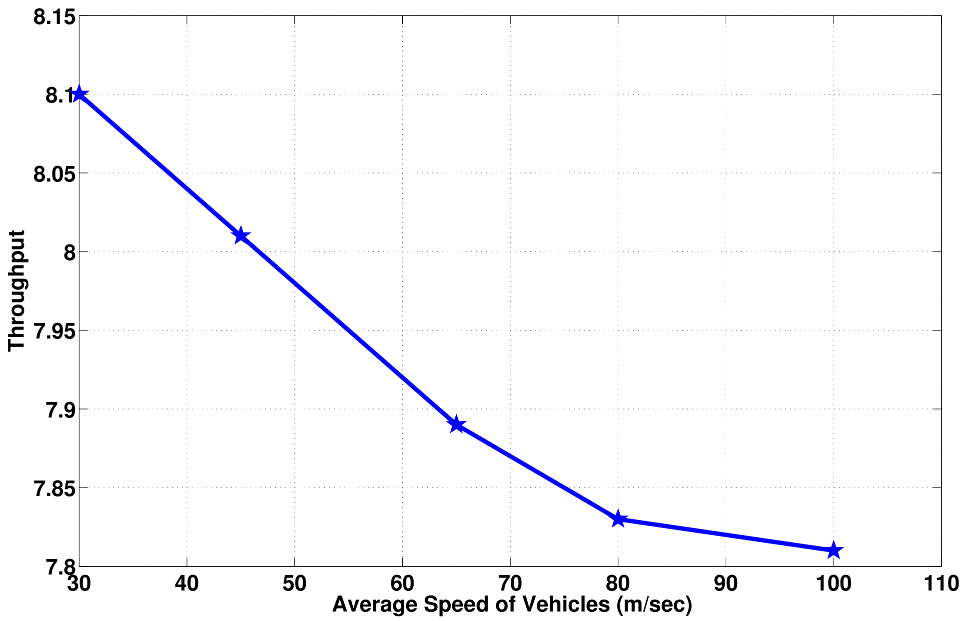


Figure 4.19: Throughput Vs Speed

get better results at higher price $p_i = 0.5$ applied at cluster sizes of 5 or less. Therefore, for an optimum use of bandwidth allocated by the RSU, better performance is achieved at higher price by achieving utility maximization for the optimum number of clusters in our network. We also investigate our proposed game at different speeds for different population sizes, such as $N = 100$ and $N = 200$. Our results conclude that the average throughput of clusters is maximized and system converges at different speeds as shown in Fig. 4.15 and Fig. 4.16. This shows that the resulting protocol is extremely efficient and robust and is capable to deal with different levels of speeds. Fig. 4.19 shows the throughput graph of clusters that shows a decrease in throughput with increasing speed. Moreover, Our proposed game is also analysed for scalability at different population sizes, such as $N = 20$, $N = 50$, $N = 100$, $N = 150$ and $N = 200$. Simulations reveal that the evolutionary convergence of the clusters in a network of different population sizes can be achieved within **hundreds of milliseconds**, as shown in Fig. 4.18. It is worth mentioning that the numbers of nodes N and heads H can be time-varying in practice. Nevertheless, given N and H, the proposed evolutionary game stabilizes fast and the clusters are formed quickly in a distributed, automated fashion. In most cases, the network topology of a VANET would have barely changed before the proposed game stabilizes. Hence, our results conclude that the average total throughput is maximized and system converges at different population sizes and therefore, we are able to get the optimum number of clusters at different population sizes as shown in Fig. 4.18. Therefore, our simulation results in Figs. 4.15, 4.16 and 4.18 reveal that the system converges at different speeds and population sizes. We also compare our proposed game with Aggregate Local mobility (ALM) [8] as an existing clustering strategy in VANETs. Our results in Fig. 4.11 clearly demonstrate that almost 40% of switching rate of nodes (change of roles from heads to member or member to heads) remains zero as compared to ALM. Moreover, using our proposed EGT, rate of switching is almost reduced by 50% as compared to ALM. Average switching rate is also reduced as compared to the compared clustering strategy as shown in Fig. 4.12. Therefore our proposed game ensures more stable clusters with increased cluster lifetime as shown in Fig. 4.11 and Fig. 4.12. Moreover, to study the complexity of our proposed protocol, we calculate the complexity of control packets exchanged between RSU and heads. The control overhead analysis is conducted using Monte Carlo method. Our simulation results in Fig. 17 show that for a given number of nodes N, the control overhead increases **logarithmically** (i.e., $\mathcal{O}(N \log_2 H)$, as the number of heads H increases. Our results also show that all cases i.e., best case, worst case and average case scale equally with the number of nodes. Hence, our proposed protocol is lightweight and computationally efficient, as the complexity of control overhead grows very slowly.

4.6 Conclusion

In this chapter, an EGT approach is proposed for FC framework for Stable and Optimized Clustering in VANETs. Our proposed framework is able to maintain cluster stability, as the clusters evolve towards balanced sizes and system is converged with an average total throughput of clusters.

The equilibrium point is proved analytically and the stability of equilibrium point is also tested using a Lyapunov function. Two performance evaluation approaches are used in this chapter, to investigate the efficiency of our proposed game under different populations and speeds.

The performance of proposed evolutionary game is empirically investigated with different cost functions using *static* and *mobile* scenarios.

It is concluded from simulation results that the proposed protocol can create more stable clustering and is able to achieve optimum clustering by using the cost function. It is also concluded from simulations that the proposed protocol is robust and is effective for different populations and speeds of vehicles.

Chapter 5

A Hybrid-Fuzzy Logic Guided Genetic Algorithm (H-FLGA) Approach for Resource Optimization in 5G VANETs

5.1 Introduction

To support diversified quality of service (QoS) demands and dynamic resource requirements of mobile users in 5G driven VANETs, network resources need more flexible and scalable resource allocation strategies. Current heterogeneous vehicular networks are designed and deployed with a connection-centric mindset with fixed resource allocation to a cell regardless of traffic conditions, and static coverage and capacity.

In this Chapter, a Hybrid-Fuzzy Logic guided Genetic Algorithm (H-FLGA) approach is proposed over our proposed 5G VANET architecture in chapter 3, to provide an efficient resource allocation in 5G driven VANETs.

The idea behind using Fuzzy logic is to make the protocol more suitable for particularly implementing customer-centric network infrastructure with varying types of service requirements. Since, fuzzy logic is flexible and tolerant of handling imprecise data and contradicting inputs, the Fuzzy Inference System (FIS) rules can handle the dynamic customer needs in a highly dynamic environment of the VANETs, by providing a flexible and optimum solution [108], [109]. The proposed protocol is flexible and is a multi-criteria scheme optimized by using the fuzzy logic. Fuzzy logic is used to make the decision on the appropriate weightage of different objectives which will help the providers to tune the protocol to work for different scenarios by modifying the fuzzy membership functions and fuzzy rules. The major contributions and the results of this chapter can be summarized as follows;

- The proposed Hybrid-Fuzzy Logic guided Genetic Algorithm (H-FLGA) allows the network service providers to implement a more customer-centric network infrastructure thus improving their spectral efficiency. The network can automatically adapt to dynamic customer needs and capacity demand fluctuations of mobile users in VANETs. To the best of our knowledge, this is the first work in the area of 5G driven VANETs, which uses a hybrid Fuzzy Logic guided GA approach for resource optimization.

- Five different scenarios of resource optimization are formulated in this chapter which focus on different network aspects, such as, capacity, minimising number of FC-BBUCs, minimising delay, the number of FC-ZCs which one BBUC handles, the traffic load of each FC-ZC and consequently of each BBUC Pool. In addition, this approach supports energy efficient optimization for service providers, as some idle BBUC's may be switched off without any adverse effect on the overall system thus reducing OpEx.

- Realizing the service oriented view, input and rules of the proposed Fuzzy Inference System (FIS) are defined, for optimizing weights of multi-objectives, depending on the Type of Service (ToS) requirements of customers. Using proposed FIS, different options are weighted and multi- objective weights are optimized, to provide the optimal solution.

- The results of the proposed hybrid H-FLGA approach are compared with the GA and the 5G driven VANET architecture in [9].

The remainder of the chapter is organized as follows: Section 5.3 provides some challenges and the key enabler technologies for 5G Driven VANETs. Section 5.4

describes formulation of resource optimization scenarios in 5G driven VANETs, section 5.5 explains details of proposed H-FLGA approach. Section 5.6 provides the results and discussions and finally, the results of the chapter are concluded.

5.2 Background and Related Work

In the recent years, VANETs are expected to utilize 5G cellular networks to deliver broadband services and enhance traffic and road safety to the users. In the next few years, there will be a dramatic increase in Machine-to-Machine (M2M) communication due to the massive diffusion of Internet of Things (IoT) traffic. This dramatic increase will boost innovation and generate economic growth across wide range of verticals such as automotive, energy, media, food and agriculture, healthcare, management, manufacturing, public transportation [110]- [111]. On the other hand, Vehicular Social Networks (VSNs) [112] are also emerging where passengers can share user centric information with each other using mobile devices and can exchange data related to infotainment, utility, and emergency services [113]- [114]. By 2020, smarter and secure Intelligent Transportation Systems (ITS) are expected to be operational as a VANET cloud [115]. With this view, the emerging scenario of VANET implementations is expected to be heterogeneous in terms of resources, network topology, contents [116] and traffic types (including legacy voice and data traffic, as well as those generated by emerging M2M connections), all with different quality-of-service (QoS) requirements [117]. Also, current heterogeneous VANET architectures using cellular systems such as 4G and recent LTE Advanced systems have been designed and deployed with a connection-centric mindset with fixed resource allocation to a cell regardless of traffic conditions, static coverage and capacity [118], [116], [119]. Furthermore, they lack in flexibility to efficiently deal with the data off-loading over different access networks [120] and to provide reconfigurability of RAN equipment to adapt to varying traffic and QoS demands of users. In order to support the exponential growth of heterogeneous mobile data traffic of new ITS applications and to support a platform for IoT applications and social networking, a radical rethink of current VANET architecture is essentially required. According to our vision, this evolution can only be achieved by turning it into a more flexible and programmable fabric, through technological improvements enabled by next generation emerging technologies like Cloud-RAN, Software Defined Networking (SDN) and Fog Computing, which can jointly be used to provide a multitude of diverse services and resource sharing over a common underlying physical infrastructure. In our previous study, we proposed a 5G driven VANET architecture in [121], which offers more flexible and programmable fabric, leveraging the concepts of SDN, C-RAN and Fog Computing. In this study, we propose a hybrid optimization approach over our 5G VANET architecture, to provide an efficient resource allocation using Fuzzy logic guided Genetic algorithm. Fuzzy logic is one of the most well-known tools used to solve problems in dynamic and constantly changing systems. To address decision making process in VANETs, fuzzy logic has been used in different scenarios such as a broadcast protocol in Vehicular Ad hoc Networks where the fuzzy logic system decides if the node is required to rebroadcast or not [108]. In [109], a fuzzy logic-based scheme is proposed in VANETs to select backbone nodes, which consider the velocity of vehicles, the number of neighboring vehicles moving in the same direction and the height of the antenna. The idea behind using Fuzzy logic is to make the protocol more suitable for particularly implementing customer-centric network infrastructure with varying type of service requirements. Furthermore, given the large number of combinations of linking FC-ZCs with BBUCs and capacity demand fluctuations, in our proposed architecture [121], an efficient resource allocation becomes increasingly difficult to tackle, using the conventional brute-force techniques. Since fuzzy logic is flexible and tolerant of handling imprecise data and contradicting inputs, using a hybrid Fuzzy logic guided Genetic Algorithm approach can provide us a better solution.

5.3 Challenges and Key enabler Technologies for 5G Driven VANETs

One of the promising techniques to support 5G cellular networks is Ultra Dense Networks (UDNs) [122], in addition to macro cells which provides wide coverage [123], [119]. By deploying more small cells in a fixed region, the average distance between the users and the BS can be significantly reduced and hence system capacity can be increased by improving the spatial reuse of radio resources. Also, to mitigate the drastic interference generated by the neighboring small cells, the inter-cell interference coordination (ICIC) scheme of current 4G cellular networks assigns different blocks of resources to cell-edge user equipment (UE) from neighboring cells. However using this scheme the Base stations cannot make effective use of resources of neighbor cells, when there are no cell-edge UEs in the neighboring cells. Hence, another challenge is to design efficient dynamic Radio Resource Management (RRM) in 5G networks which will adapt to distinct traffic and interference variations in small cells [123]. Different approaches namely auction based [124], optimization based [125], demand supply based [126], Evolutionary Game Theoretic (EGT) based [19] are applied to solve different optimization problems in heterogeneous wireless access networks and VANETs. Furthermore, current Heterogeneous VANET (Het-VANETs) implementations allocate fixed resources to a cell regardless of traffic conditions in other cells. To achieve these goals in 5G VANETs, more flexible and optimal resource allocation methodologies must be devised to enhance network capacity for highly mobile users, by keeping in view the different QoS requirements of users.

Also, mobile operators are constrained by the inflexibility and reconfigurability of Radio Access Network (RAN) equipment with respect to distinct traffic and QoS demands of users. To meet these challenging requirements a revolution of technologies in both Radio access networks and the mobile core network is required. Cloud-RAN has recently been identified as a leading candidate for 5G mobile network architecture which enables the sharing of network resources in a centralized data center, being cost-effective to operators, and enhances the spectrum efficiency of next generation networks [119], [127]. In C-RANs, a large number of low-cost Remote Radio Heads (RRHs) are randomly deployed and connect to the Base Band Unit (BBU) pool through the fronthaul links. The operations of RRHs and the computing resources of the BBU pool can be dynamically controlled in order to adapt to the capacity demand fluctuations, which leads to significant reductions in capital expenditures (CapEx) and operating expenses (OpEx) with much higher growth of revenue [46]. Additionally, C-RAN also allows integration of Long-Term Evolution Advanced (LTE-A) technologies and evolutions of novel 5G radio access and WiFi [80]. On the other hand, Software Defined Networking (SDN) has emerged as one of the possible solutions for combining the management of base stations and access networks due to the separation of control and data plane [3]. In an SDN-enabled network, all devices are managed and controlled by a centralized controller, and the network operators can dynamically assign network virtualization strategies and forwarding rules to the controller instead of defining rules at different devices [128]. In addition, SDN allows operators to quickly configure and deploy new network services and provide fine-grained traffic engineering control for each user, using a policy-based management paradigm running on commodity hardware. For example, bandwidth allocation can be dynamically designed by operators on a per-flow basis instead of using generic origin-destination criteria [129] and operators can employ different policies for diversified service demands of users.

In 5G C-RANs, resource allocation and the RRH-BBU mapping problem has been addressed in a number of research works in the literature [130]- [131], However, in [130] a dynamic RRH-BBU mapping algorithm is developed. However, the service provider's profit is not a focus of attention. Similarly a resource allocation problem with a bargaining solution is proposed in [132] by employing the newsvendor game model. However, this scheme requires additional time for resource reconfiguration, which can deteriorate QoS requirements. In SDN based VANETs, resource management and allocation are very important since they can significantly affect the QoS and resource utilization. However, the relationship between QoS satisfaction and resource limitation including the interaction among various types of resources have not yet been fully studied, due to the new hierarchical framework of SDN [133]. There is a need to develop flexible and scalable resource allocation strategies to support diversified QoS demands in VANETs.

Furthermore, the Ultra-Dense Networks (UDN) are also envisioned to be a highly promising technology used to enhance network capacity and spatial multiplexing. Some state-of-the-art research works in UDN and Computation offloading in the field of VANETs can be found in [134], [135]. The authors study the MECO problem in UDN and propose a heuristic greedy offloading scheme [136].

Furthermore, collectively SDN and C-RAN will provide service providers with an opportunity to implement a more customer-centric network infrastructure, where the network can automatically adapt to dynamic customer needs and capacity demand fluctuations of users in VANETs. The success of virtualization and cloud technologies provides one of the possible solutions. However, there are many directions needed to investigate to support SDN based VANETs. SDN based migration is inevitable and unless a network is built from scratch, there is a need to manage both legacy and SDN based framework ensuring service delivery and performance across all domains. The key to all of this is going to be the availability of interoperable virtual network functions (VNFs). Furthermore, due to the exchange of security related data between the vehicles and the RSUs over a separate channel also impose different challenges such as identity protection and data integrity because of the expected heterogeneous network architecture in 5G networks [137].

Recently, Mobile Edge Computation offloading (MECO) is also emerging as a key technology toward 5G to achieve lower latency and higher reliability [138]. However, the existing MECO research only focus on the resource allocation between the Mobile devices (MDs') and the MEC servers and ignored the huge computation resources in the centralized cloud computing centers. With increase in growth of mobile applications and MDs', the resource bottleneck of MEC servers has been becoming more and more prominent, and is affecting the network operators' capital expenditure (CapEx) and operating expense (OpEx). In [138] the problem of collaborative computation offloading with centralized cloud and multi-access edge computing is studied. Similarly in [139], they studied the collaborative task offloading problem in vehicular edge computing networks to fully utilize the computing resources of the remote cloud center and MEC servers. In [140], a distributed and adaptive resource management controller is designed and tested, which allows the optimal utilization of Cognitive Radio and soft-input/soft-output data fusion in VANETs

In our opinion, since fuzzy logic is based on natural language and is tolerant of handling imprecise data, hence, combining Fuzzy logic with GA can provide us with a better solution for optimal resource utilization in VANETs. Furthermore, in a highly dynamic VANET environment, an optimal solution is dependent on the network environment such as bandwidth, vehicle mobility and link status. The solutions based on any mathematical modelling are non-flexible and complex to derive for rapidly changing environments [141], [142]. Therefore, we use a hybrid approach using Fuzzy Logic guided Genetic Algorithm for optimum resource allocation in 5G driven VANETs. Our proposed Fuzzy Inference system (FIS) is used to optimize weights of multi-objectives. These optimized weights are then used by Genetic Algorithm to optimize connections between BBUCs and FC-ZCs.

5.4 Resource Optimization in 5G Driven VANETS

We propose an extension of our previously proposed 5G Next generation VANET architecture [9]. In our proposed architecture, there are Fog Computing-Zone Controllers (FC-ZCs), Fog Computing BBU Controllers (FC-BBUCs), Fog Computing-Cluster-Heads (FC-CHs) and Fog Computing-Vehicles (FC-Vehicles). The purpose of this study is to optimize the allowable connections between FC-ZCs and FC-BBUCs and also to support cost and energy efficiency by switching off the idle FC-BBUCs. In this section, we formulate five different scenarios of network resource optimization in 5G driven VANETs.

Problem Formulation

Let $ZC = \{ZC_1, ZC_2, ..., ZC_n\}$ with cardinality $|ZC| = n_{ZC}$ represents the set of Fog Computing Zone Controllers (FC-ZCs) which are distributed in an area. n_{ZC} is the number of FC-ZCs and n_{BBUC} represents number of Fog Computing BBU Controllers (FC-BBUCs). Let $BBUC = \{BBUC_1, BBUC_2, ..., BBUC_n\}$ with cardinality $|BBUC| = n_{BBUC}$ represent the set of FC-BBUCs, such that $n_{BBUC} \leq n_{ZC}$. Let $Links = \{BBUC_i, ZC_j\}$ represents the set of possible link pairs between FC-BBUCs and FC-ZCs.

Variables

$$Z_{ij} = \begin{cases} 1, & if \quad ZC_j \quad is \quad served \quad by \quad BBUC_i \\ 0, & otherwise \\ where(i,j) \in Links \end{cases} \tag{5.1}$$

$$Y_i = \begin{cases} 1, & if \quad BBUC_i \quad is \quad Chosen \\ 0, & otherwise \end{cases} \tag{5.2}$$

5.4.1 Minimise the number of FC-BBUCs (Min-BBUC)

The objective of this problem is to minimize the number of FC-BBUCs serving FC-ZCs which are requesting for resources as shown in Fig. 5.1. It is assumed that FC-ZCs can connect to any of the BBUC pools, which means that there are no restrictions concerning distance. Given as an input data to the problem includes: the capacity row vector for BBUCs, capacity demand row vector for FC-ZCs and a binary link matrix indicating allowable connections between BBUCs and FC-ZCs.

Objective function

The objective function is given by

$$\text{Minimize } C_{n_{BBUC}} = \sum_{i=1}^{n_{BBUC}} C_{BBUC_i} Y_i \tag{5.3}$$

where n_{BBUC} is the number of FC-BBUCs in the pool, C_{BBUC_i} is i_{th} element with a value equal to the total available capacity (Aggregated Link Capacity) of FC-BBUCi in capacity row vector C_{BBUC}.

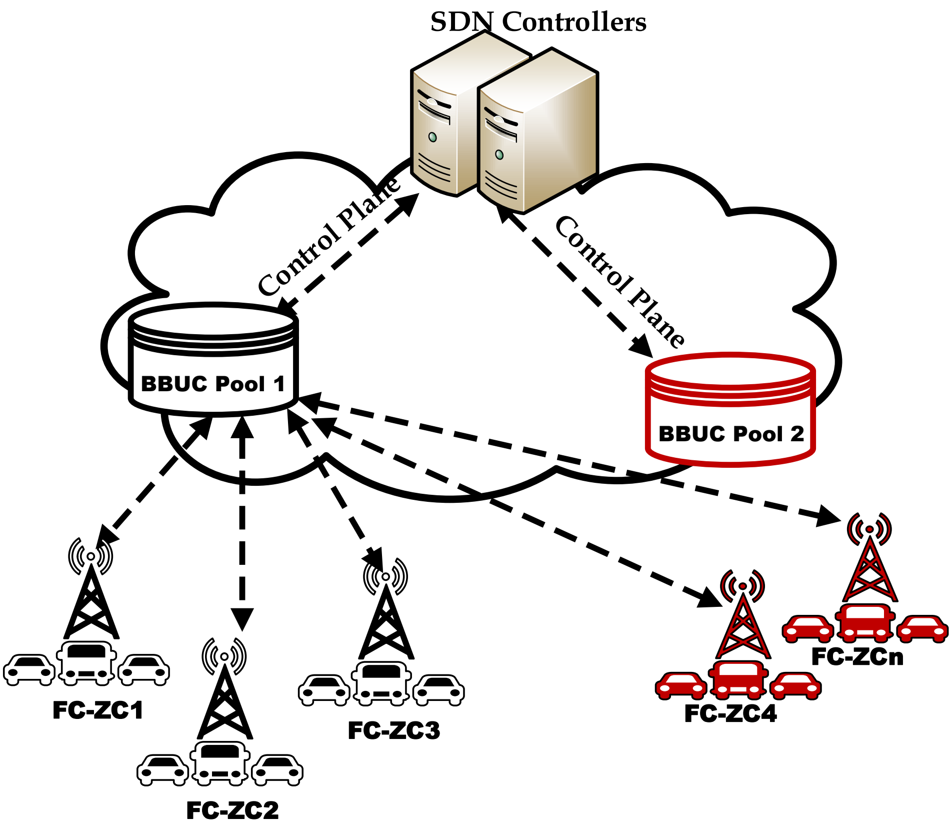


Figure 5.1: Minimize number of BBUC pools

5.4.2 Minimize Delay (Min-Delay)

The objective of this problem is to minimize the delay by connecting FC-ZCs closer to the possible BBUC Pool location, as illustrated in Fig. 5.2 by using the Min-Delay algorithm. The SDN controller has all the possible locations of BBUC pools, thus, knowing all the distances between possible link connections between FC-ZC and BBUC. Given as an input data to the problem is the available capacity row vector for BBUCs, capacity demand row vector for FC-ZCs, a binary link matrix indicating allowable connections between FC-ZCs and BBUCs and cost associated with each link. Since, the delay is considered to be directly proportional to the distance between FC-ZCs and BBUCs which in turn is related to the cost associated with linking BBUC and FC-ZCs.

Objective function

The objective function is given by

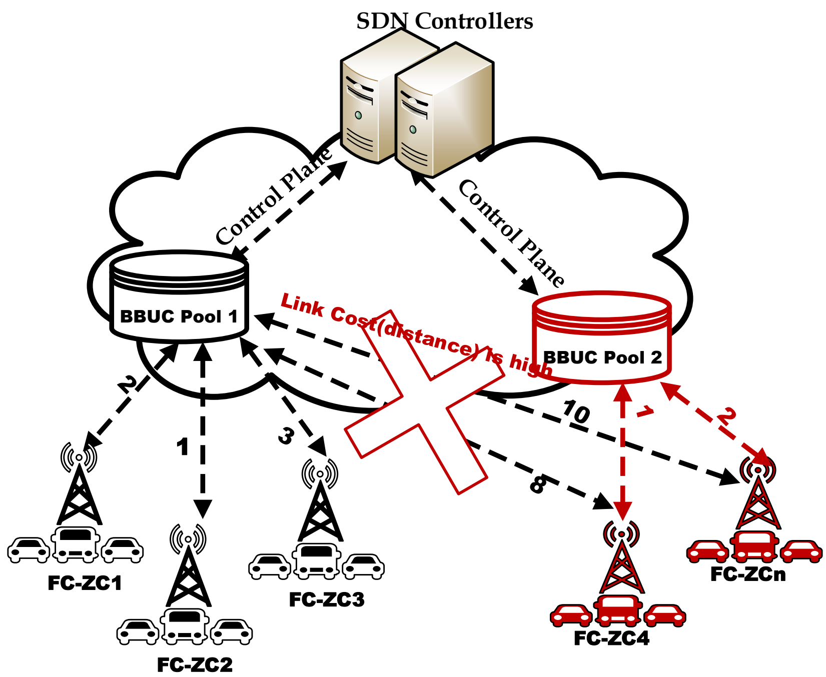


Figure 5.2: Minimize Delay

$$\text{Minimize } C_{Delay} = \sum_{i=1}^{n_{BBUC}} \sum_{j=1}^{n_{ZC}} Cost_{i,j} Z_{ij} \tag{5.4}$$

where n_{BBUC} is the number of BBUCs in the pool, $Cost_{i,j}$ is the link cost for linking ZCs j and $BBUC_i$ in the cost matrix $Cost$.

5.4.3 Capacity Load Balance(Cap-LB))

The Cap-LB algorithm aims to balance the traffic load in every BBUC Pool. The information of traffic load of each BBUC Pool is always available and updated by the SDN controller. Before evaluating the decision, the controller has the information of traffic load of the possible BBUC Pool connections. Thus, the controller will check not only the maximum capacity limit of the BBUC Pool, but also the possible load on the BBUC pool. With this approach, as illustrated in Fig. 5.3, it is guaranteed that the BBUC pools have a capacity balance in what concerns to traffic load.

Objective function

The objective function is given by

$$\text{Minimize } C_{cap_L} = \frac{1}{n_{BBUC}} \sqrt{\sum_{i=1}^{n_{BBUC}} (D - D_i)^2} \tag{5.5}$$

where $D_i = \sum_{j=1}^{n_{ZC}} Z_{ij} C_{ZC_j}$ is i^{th} element indicating the total load demand in BBUCi in the total load demand vector D and $D = \frac{1}{n_{BBUC}} \sum_{i=1}^{n_{BBUC}} D_i$ is the average load demand across all BBUCs. The idea behind the objective function is to reduce the standard deviations of the total load demand vector D. Under ideal conditions, if the load demand is the same in all BBUCs, the positive objective function value must be equal to zero.

5.4.4 Number of FC-ZCs per BBUC Balance Algorithm (FC-ZC-per-BBUC-Bal)

The objective of this problem is to balance the number of connections to BBUCs serving FC-ZCs which are requesting for resources using the FC-ZC-per-BBUC-Bal algorithm. Under ideal conditions, the algorithm should produce a connection arrangement for BBUCs and FC-ZCs such that the number of FC-ZCs in every BBUC should be balanced as illustrated in Fig. 5.4. The information on the number

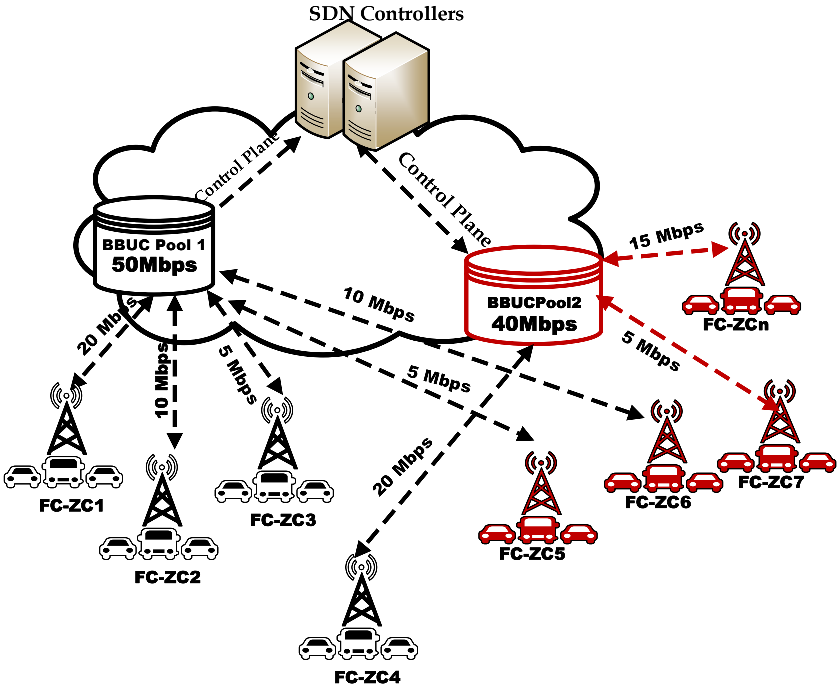


Figure 5.3: Capacity Load Balance

of FC-ZCs which each BBUC pool has, is always available and updated by the SDN controller.

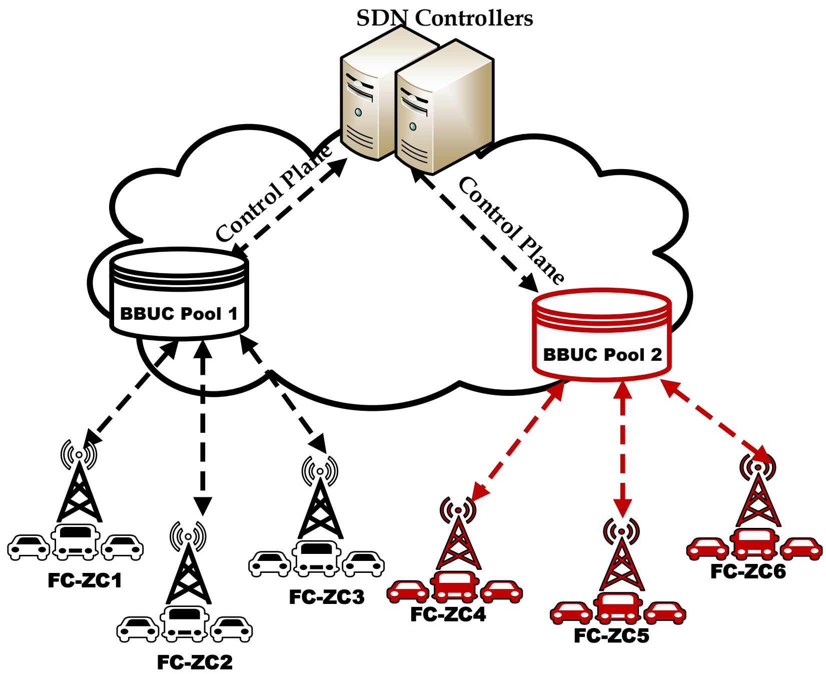


Figure 5.4: Number of FC-ZC per BBUC Balance

Objective function

The objective function is given by

$$\text{Minimize } C_{ZC_{per_{BBUC}}} = \frac{1}{n_{BBUC}} \sqrt{\sum_{i=1}^{n_{BBUC}} (N - N_i)^2} \tag{5.6}$$

where $N_i = \sum_{j=1}^{n_{ZC}} Z_{ij}$ is the i^{th} element indicating the total number of FC-ZCs connected to $BBUC_i$ in the total connections vector N and $N = \frac{1}{n_{BBUC}} \sum_{i=1}^{n_{BBUC}} N_i$ is the average number of FC-ZCS connected across all BBUCs. The idea behind the objective function is to reduce the standard deviations of the total connections vector N. Under ideal conditions, if the number of connection is the same in all BBUCs, the positive objective function value must be equal to zero.

Constraints for Problem 5.4.1, 5.4.2, 5.4.3, 5.4.4

Problems 5.4.1, 5.4.2, 5.4.3, 5.4.4 are subject to the following constraints:

1. The Fog Computing Zone Controller ZC j should atleast be connected to one FC-BBUC.

$$\sum_{i=1}^{n_{BBUC}} Z_{ij} = 1 \tag{5.7}$$

$\forall j \epsilon \{1, 2, ..., n_{ZC}\}$ and $\forall (i, j) \epsilon Links$. n_{ZC} is the number of FC-ZCs and Z_{ij} is an element of link matrix Z whose value is 1 or 0 if ZC j is connected to $BBUC_i$ or otherwise, respectively.

2. Sum of link capacity demands of ZCs which are connected to the BBU controller BBUC i, must be less than or equal to the available link capacity of BBUC i.

$$\sum_{j=1}^{n_{ZC}} Z_{ij} C_{ZC_j} \leq C_{BBUC_i} \tag{5.8}$$

$\forall j \epsilon \{1, 2, ..., n_{ZC}\}$ and $\forall i \epsilon \{1, 2, ..., n_{BBUC}\}$. C_{ZC_j} is j^{th} element with a value equal to the capacity demand for ZC j in capacity demand row vector C_{ZC}.

3. BBUC i should be serving if atleast one FC-ZC is connected to it.

$$Z_{ij} \leq Y_i \tag{5.9}$$

$\forall j \epsilon \{1, 2, ..., n_{ZC}\}$ and $\forall i \epsilon \{1, 2, ..., n_{BBUC}\}$.

4. BBUC i should not be serving if no FC-ZCs are connected to it.

$$\sum_{j=1}^{n_{ZC}} Z_{ij} \geq Y_i \tag{5.10}$$

$\forall j \epsilon \{1, 2, ..., n_{ZC}\}$ and $\forall i \epsilon \{1, 2, ..., n_{BBUC}\}$.

5.4.5 Constant Traffic Load (CTL)

CTL algorithm aims to force a constant traffic profile in every BBUC Pool, with the objective to avoid traffic peaks, taking into consideration the three types of FC-ZCs: Residential FC-ZCs, Commercial FC-ZCs and Mixed FC-ZCs as illustrated in Fig. 5.5. Each FC-ZC has different traffic behavior throughout the day. To obtain multiplexing gains and energy efficiency in a Cloud-RAN approach, as compared to traditional RAN, an ideal BBUC Pool traffic profile should have a constant traffic load throughout the day. This algorithm takes the selected hours of the day as input parameters (i.e. a vector of integers ranging between 1 and 24). Since the information on the traffic profile of each BBUC Pool is always available and updated by the SDN controller. Before evaluating the decisions, the controller evaluates the possible connections, by using a vector of hours. The controller establishes the connection with BBUC Pool by considering the traffic load. This problem addresses a time-series type of problem where the capacity demand of all the FC-ZCs are given with respect to time (demand vs time (duration in hours)). Using CTL, it is very effective to turn off some idle BBUC's without any adverse effect on the overall system thus consuming energy efficiently. Given as input data to the problem is the capacity row vector for BBUCs, time-series capacity demand matrix for FC-ZCs, a binary link matrix indicating allowable connections between BBUCs and FC-ZCs and cost associated with each link.

Objective function

The objective function is given by

$$C_{CTL} = \sum_{i=1}^{n_{BBUC}} BTD_i \tag{5.11}$$

where $P_i = [Z_{i \times n_{ZC}}, Z_{i \times n_{ZC}}, ...]^T$ for $i \epsilon \{1, 2, ..., n_{BBUC}\}$; $Q_i = P_i \times C_{ZCH}$ for $i \epsilon \{1, 2, ..., n_{BBUC}\}$; $R_i = \sum_{j=1}^{n_{ZC}} q_j$ for $i \epsilon \{1, 2, ..., n_{BBUC}\}$ and q_j is the j^{th} column vector in Q_i; and

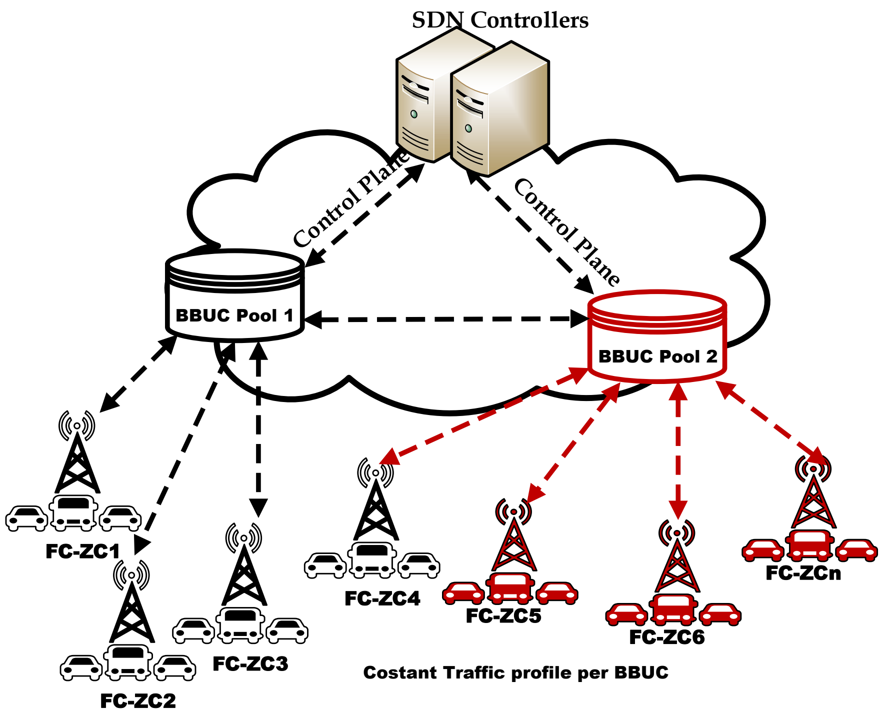


Figure 5.5: Constant traffic load per BBUC

BTD_i = standard deviation of R_i for $i\epsilon\{1, 2, ..., n_{BBUC}\}$. R_i column vector essentially contains the total demand in the $BBUC_i$ with each row corresponding to a duration interval. BTD_i is the i^{th} value indicating the standard deviation of the variation of total demand in $BBUC_i$ during the course of its operation in BBUC traffic deviation vector BBU-Traffic-Dev BTD.

Constraints

1. ZC j should at least be connected to one BBUC.

$$\sum_{i=1}^{n_{BBUC}} Z_{ij} = 1 \tag{5.12}$$

   where $j\epsilon\{1, 2, ..., n_{ZC}\}$ and $(i, j)\epsilon Links$. Z_{ij} is an element of link matrix Z whose value is 1 or 0 if ZC_j is connected to $BBUC_i$ or otherwise, respectively.

2. Sum of capacity demands of FC-ZCs connected to BBUC i must be less than or equal to the available capacity of that BBUC i.

$$\sum_{j=1}^{n_{ZC}} Z_{ij} C_{ZC_j}(Z, C_{ZCH}) \leq C_{BBUC_i} \tag{5.13}$$

where $j\epsilon\{1, 2, ..., n_{ZC}\}$ and $i\epsilon\{1, 2, ..., n_{BBUC}\}$. C_{ZC_j} is j^{th} element with a value equal to the capacity demand for ZC_j in capacity demand row vector C_{ZC} of size $1 \times n_{ZC}$. C_{ZCH} is also a function of the link matrix Z and the capacity demand matrix for FC-ZCs for all the durations. The capacity demands corresponding to each FC-ZC in the C_{ZC} are selected by the SDN controller as follows;

- Find the R_i for each BBUC i. Note the FC-ZC connected to that BBUC i.
- Find the position of the peak demand in R_i.
- Use the same position to choose the CZC value for the connected FC-Zcs to $BBUC_i$ from the C_ZCH matrix. Repeat for all BBUCs till all the elements in C_ZC capacity demand vector are obtained.

3. BBUC i should be serving if at least one FC-ZC is connected to it.

$$Z_{ij} \leq Y_i \tag{5.14}$$

where $j\epsilon\{1, 2, ..., n_{ZC}\}$ and $i\epsilon\{1, 2, ..., n_{BBUC}\}$.

4. BBUC i should not be serving if no FC-ZCs are connected to it.

$$\sum_{j=1}^{n_{RRH}} Z_{ij} \geq Y_i \tag{5.15}$$

where $j\epsilon\{1, 2, ..., n_{Zc}\}$ and $i\epsilon\{1, 2, ..., n_{BBUC}\}$

5.4.6 Multi-Objective Optimization

The multi-objective function is mathematically the algebraic sum of the post-operated individual objective function with the possible lower limit of the value 0 and an upper limit of the value of 1. For the purpose of creating an impartial multi-objective function, each of the individual objective functions described in previous sections is normalized with respect to a factor (so as to obtain a minimum and maximum value of 0 and 1, respectively) and a weight of unity is assigned to each individual objective function to demonstrate equal importance to each of the objectives. The inputs of the problem include link capacity of BBUCs, time-series demands of FC-ZCs, a binary link matrix indicating allowable connections between BBUCs and FC-ZCs and the cost associated with each link. The Objective functions from the previous sections are given as

$$\begin{aligned} C_1 &= \sum_{i=1}^{n_{BBUC}} C_{BBUC_i} Y_i \\ C_2 &= \sum_{i=1}^{n_{BBUC}} \sum_{j=1}^{n_{ZC}} Cost_{ij} Z_{ij} \\ C_3 &= \frac{1}{n_{BBUC}} \sqrt{\sum_{i=1}^{n_{BBUC}} (D - D_i)^2} \\ C_4 &= \frac{1}{n_{BBUC}} \sqrt{\sum_{i=1}^{n_{BBUC}} (N - N_i)^2} \\ C_5 &= \sum_{i=1}^{n_{BBUC}} BTD_i \end{aligned} \tag{5.16}$$

Hence, the multi-objective function can be formulated as the algebraic sum of normalized individual objectives functions with a weightage factor. It is given by

$$min\ C_{obj} \tag{5.17}$$

where

$$\begin{aligned} C_{obj} = &\omega_1 \frac{C_1 - C_{1,min}}{C_{1,max} - C_{1,min}} + \omega_2 \frac{C_2 - C_{2,min}}{C_{2,max} - C_{2,min}} + \\ &\omega_3 \frac{C_3 - C_{3,min}}{C_{3,max} - C_{3,min}} + \omega_4 \frac{C_4 - C_{4,min}}{C_{4,max} - C_{4,min}} + \\ &\omega_5 \frac{C_5 - C_{5,min}}{C_{5,max} - C_{5,min}} \end{aligned} \tag{5.18}$$

where C_1, C_2, C_3 and C_4 are the Objective functions for the objectives laid out in Sections 5.4.1, 5.4.2, 5.4.3, 5.4.4 and 5.4.5, respectively. In Equation 5.18, the max and min subscripts indicate the maximum and minimum values, respectively, for the objective functions when optimized individually. It is necessary to normalize the cost function values for each individual objective function between 0 and 1. $\omega_1, \omega_2, \omega_3, \omega_4$ and w_5 are the weightage factors for each individual objective functions. Importance to any objectives can be increased or decreased by the service providers, by altering these values, depending on the dynamic customer needs and capacity demand fluctuations of users in VANETs. We use Fuzzy Logic to find these weights.

5.5 Hybrid-Fuzzy Logic guided Genetic Algorithm (H-FLGA)

We propose a Hybrid-Fuzzy Logic guided Genetic Algorithm (H-FLGA) approach for SDN controller which solves a multi-objective optimization problem. Different objectives are combined to assign most accurate practical connection arrangement between BBUCs and FC-ZCs. Depending on the Type of Service (ToS) requirements of customers, different options are weighted and optimized using Fuzzy Inference System (FIS) and then used by GA to provide optimal solution.

Fuzzy Inference System (FIS)

Fig. 5.6 illustrates the flow chart of proposed algorithm. The fuzzy system has two inputs; Type of service (ToS) and value ($Value$). ToS is the requirement of customers based on three parameters i.e., Throughout, Delay and Cost. The outputs of FIS is priorities coefficients ω_i for optimized weights of the multi-objectives. Hence, $\omega = f(Tos, Value)$ where $ToS = \{Delay(D), Throughput(T), Cost(C)\}$ and $Value = \{0, 1\}$. The outputs are in the range in $[0, 1]$. We choose the Gaussian membership function for the inputs and outputs variables. Tables 5.1 and 5.2 show the possible ToS values and ToS *vs.* Priority of ω_i. To define the rules for each output, we follow the information in tables 5.1 and 5.2.

Rules

The rules for ω_i are as follows;

$r1 \ =' if\ ToS\ is\ D\ and\ Value\ is\ zero\ then\ \omega_1\ is\ zero';$

$r2 \ =' if\ ToS\ is\ D\ and\ Value\ is\ not\ zero\ then\ \omega_1\ is\ zero';$

$r3 \ =' if\ ToS\ is\ T\ and\ Value\ is\ zero\ then\ \omega_1\ is\ medium';$

$r4 \ =' if\ ToS\ is\ T\ and\ Value\ is\ not\ zero\ then\ \omega_1\ is\ high';$

$r5 \ =' if\ ToS\ is\ C\ and\ Value\ is\ zero\ then\ \omega_1\ is\ medium';$

$r6 \ =' if\ ToS\ is\ C\ and\ Value\ is\ not\ zero\ then\ \omega_1\ is\ high';$

Table 5.1: Possible Type of Service (ToS) Values

Type of Service (ToS)	**Delay (D)**	**Throughput (T)**	**Cost (C)**
Normal	0	0	0
Low	1	-	1
High	-	1	-

Table 5.2: Type of Service (ToS) Vs. Priority ω for Fuzzy Inference System

ToS / Priority ω	**Delay D**	**Throughput T**	**Cost C**
Min-BBUC(ω_1)	0/Zero	0/Medium	0/Medium
	1/Zero	1/High	1/High
Cap-LB (ω_2)	0/Low	0/Medium	0/Low
	1/Low	1/Medium	1/Low
Min-Delay (ω_3)	0/High	0/Low	0/Low
	1/High	1/Low	1/Zero
FC-ZC-per-BBUC-Bal (ω_4)	0/Low	0/Medium	0/Low
	1/Low	1/Medium	1/Low
CTL (ω_5)	0/Low	0/Medium	0/Medium
	1/Low	1/Medium	1/High

In the same manner, we define the rules for ω_2, ω_3, ω_4 and ω_5.

After the application of the Fuzzy Inference System, the re-evaluation part of GA is executed where the fitness of the population is computed using multi objective functions with the new weights. Details about different objectives are discussed in section 5.4.

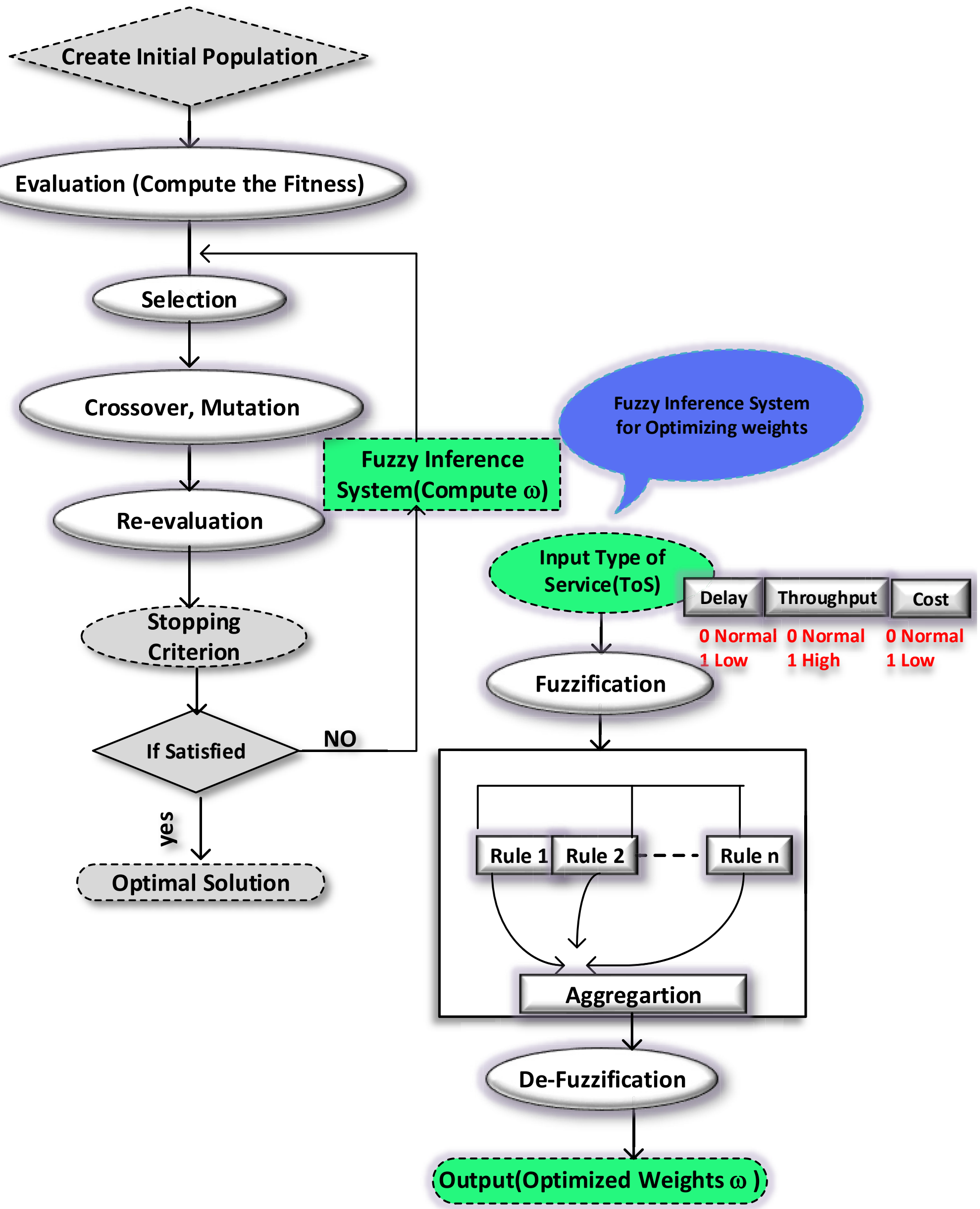


Figure 5.6: Flow Chart of Hybrid-Fuzzy Logic Guided Genetic Algorithm (H-FLGA)

Algorithm 1 : H-FLGA

Input: link capacity of BBUCs', demands of FC-ZCs, threshold of critical demands, Type of Service (ToS) and priority $Value$

Output: Optimized weights ω_1, ω_2, ω_3, ω_4, ω_5, Optimized multi objectives (C_1, C_2, C_3, C_4, C_5)

Methods: evalfis(), H-FLGA()

H-FLGA:

(1) choose a max generation number G_{MAX} and the cycle size C, set $t = 0$,

(2) Initialize randomly the population

(3) Compute the fitness for each individual in the population,

(4) Extract and save the current best individual in the population,

(5) **if** $t \leq G_{MAX}$ Stop,

else set $t = t + 1$ and continue to step (5)

(6) Apply selection, crossover and mutation,

(7) **if** $mod(t, C) \neq 0$ back to step (2)

else Call Fuzzy Inference System (FIS) to compute new weights

(8) end

Complexity Analysis

We discuss the complexity of proposed algorithm with respect to algorithm complexity of the proposed H-FLGA including the signaling overhead on the controller. The complexity of the proposed approach is a function of GA and FIS denoted by $f(\mathcal{O}(GA)\ \mathcal{O}(FIS))$. $\mathcal{O}(GA)$ depends on the operations: generate the first generation, selection, crossover, mutation and find the best individual. In addition, it also depends on the number of generations G_{MAX}. In the case of integer optimization these operators are simpler to implement. Therefore, $\mathcal{O}(GA)$ mainly depends on the complexity of the multi-objective cost function $\mathcal{O}(C_{obj})$ and the number of maximum generations G_{MAX}. Furthermore, $\mathcal{O}(FIS))$ depends on the number of cycles n_c of FIS. Hence, the combined complexity of the proposed algorithm can be expressed as $\mathcal{O}(n_c G_{MAX} \mathcal{O}(C_{obj}))$. It is seen from results in Fig. 5.7 that the objective is optimized between first 20 generations. Hence, we conclude that the proposed algorithm is efficient and lightweight.

Signaling Overhead

To analyze the signaling overhead on the controller, we consider a graph $G := (n_{BBUC}, n_{ZC})$ comprising a set n_{ZC} of vertices together with a set $n_{BBUC} \subset n_{ZC} \times n_{ZC}$ of edges. There are a total of $n_{BBUC}^{n_{ZC}}$ possible configurations of signalling. Let the average number of *BBUC-Controller* control packets be represented by S. Then the total number of subsets of S is given by 2^S. Equating the total possible configurations of signaling to the total number of subsets of S, we get

$$2^S = n_{BBUC}^{n_{ZC}}$$
$$S \approx n_{ZC} \log_2(n_{BBUC}) \tag{5.19}$$

Hence, the signaling overhead on controller is $\mathcal{O}(n_{ZC} \log_2(n_{BBUC}))$. This shows that the control overhead on the controller will increase logarithmically, as n_{BBUC} increases. Hence we conclude that, the complexity of signaling overhead on the controller will grow very slowly.

5.6 Simulation Results and Discussions

The results for the proposed algorithm are simulated using MATLAB 2017b. We used evalfis() to implement the Fuzzy Logic rules. The details of the FIS rules and simulation parameters are provided in Table 5.2 and 5.3 respectively. We perform a comparison of multi-objective optimization using the GA and the proposed H-FLGA approach. The main metric for assessing the proposed algorithm is the value of the multi-objective cost function that should lie between 0 and 5 as seen from equation 5.18 using the proposed hybrid H-FLGA approach. We test our results by optimizing the weights of different objectives in equation 5.18. These objectives indirectly relate to five different resource optimization scenarios focusing on different network aspects discussed in detail in section 5.4. First, we run the GA to solve multi-objective optimization problem in Equation 5.18 with fixed values of weights ω_i where we assume that all of them are equal to one, by considering all cost functions C_1 to C_5 as of equal importance. Fig. 5.8a to Fig. 5.8c show the results of Min-BBUC. Our results show when ω_1 is set to 1 by keeping capacity constraints under consideration, the utilization of capacity is optimized and consequently the

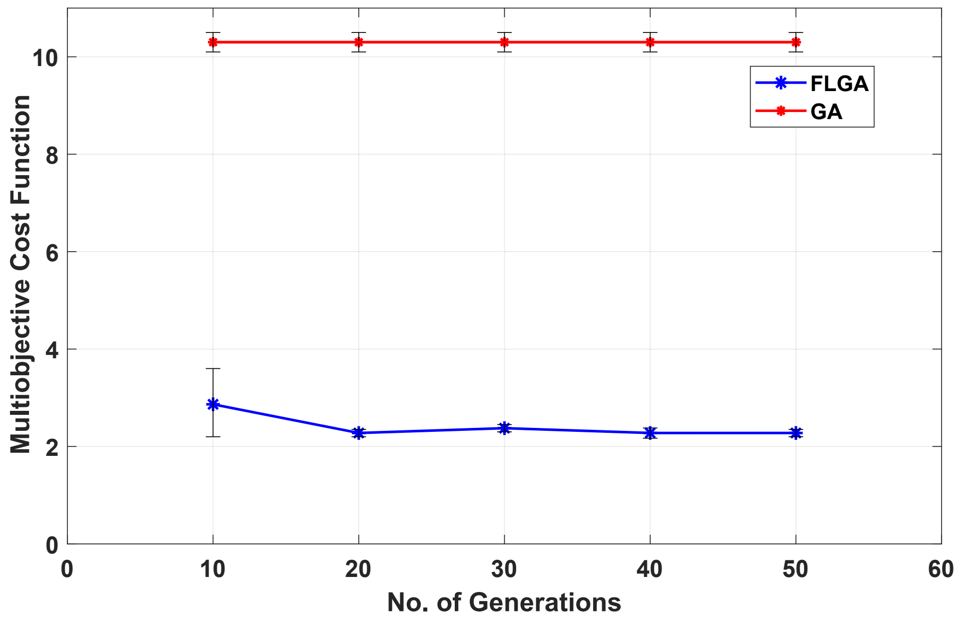
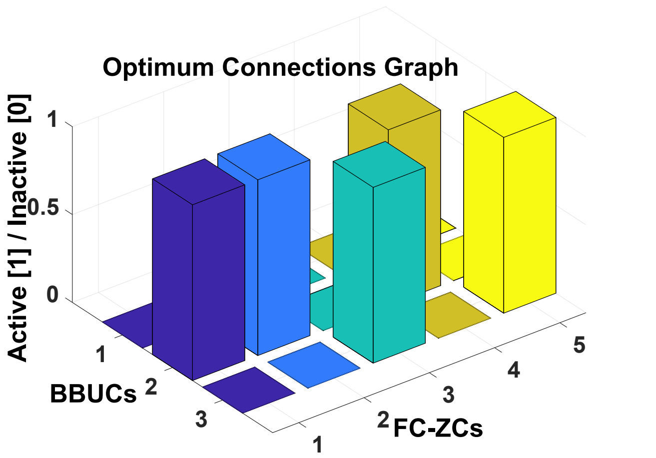


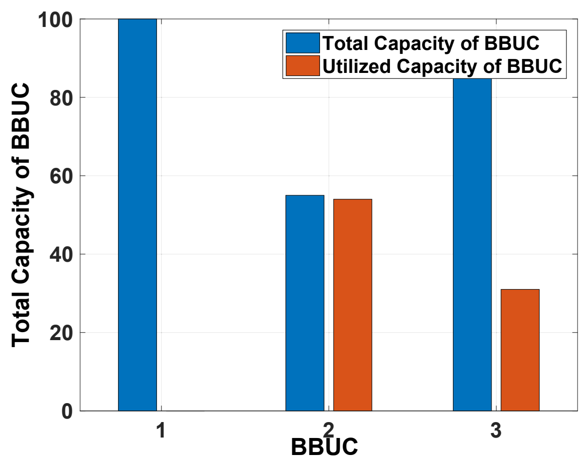
Figure 5.7: Variation of multi-objective function value for different numbers of generations

number of BBUs are minimized. Fig. 5.9a to Fig. 5.9c show the results of Cap-LB, when ω_3 is set to 1 considering the constraints defined for Cap-LB. Fig. 5.10a to Fig. 5.10c show the results of FC-ZC-per-BBUC-Bal, when ω_4 is set to 1 considering the constraints defined for FC-ZC-per-BBUC-Bal. Similarly Fig. 5.11a to Fig. 5.11c show the results of CTL, when ω_5 is set to 1 considering the constraints defined for CTL. Fig. 5.7 shows the variation of the objective function for the most optimized parameters using the H-FLGA approach. In the current study, a population size of 1000 was used for each generation and the number of generations were increased from 10 to 50 with an increment of 10. It is observed, increasing the number of generations optimizes the objective function value however, beyond 10 generations it is observed that the function value remains more or less the same. Also, a statistical study was carried out to determine the 95% confidence in the obtained solution with the algorithm. It is observed that with lower generations, there is likely to be more variation in the result, however, beyond 10 generations the confidence of obtaining the optimum value is very high as there is no varying interval on those data points. The value of cost function using GA is optimized to 10.32 and as the best score of the multi-objective function. Whereas, the best score of multi-objective function should be between 0 and 5 as seen from equation 5.18. Therefore, GA could not optimize the value of multi-objective cost function. Hence, to improve the results of multi-objective cost function, we run our proposed hybrid H-FLGA approach as a tool to optimize the weights in the multi-objective function. The results in Fig. 5.7 shows the value of multi-objective cost function is minimized and is reduced to an optimized value of 2.2 using the proposed H-FLGA. The results in Figs. 5.12a to 5.12c show how different objectives are optimized using H-FLGA. Therefore, our results in Fig. 5.7 prove that our proposed H-FLGA approach performs better when compared with GA. This is because, the value of multi-objective cost function is reduced and minimized from 10.32 to 2.2 when we applied our proposed FIS rules. It is worth mentioning that the value of optimized weights may vary depending on the TOS values defined in FIS rules. Hence, depending on ToS requirements of different customers, service providers can implement different FIS rules for different objectives and assign different priorities of *Low*, *Medium* and *High* to TOS parameters and get optimized weights. Hence, we conclude that our proposed hybrid H-FLGA approach performs better than GA and is flexible to set weights of multi-objectives, depending on QoS demands and requirements of different users.

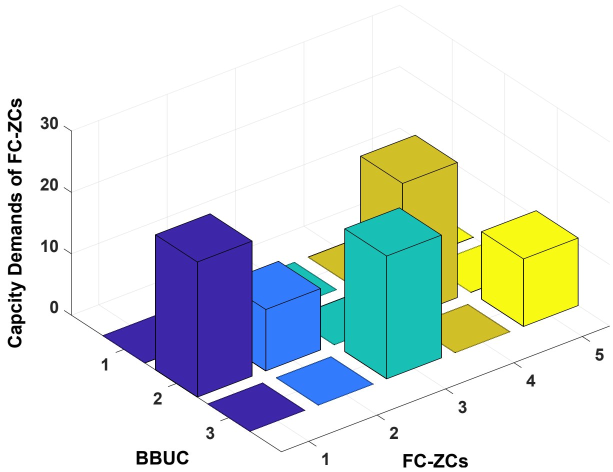
Fig. 5.13 shows the variation of the end-to-end delay for the vehicles within a maximum front-haul distance of $40km$ using three schemes- H-FLGA, GA and [121]. The number of vehicles counts is increased from 50 to 300 with varying speeds. The delay is the highest using [121] while lowest using the proposed H-FLGA. For each data point in the graph, vertical markers are used to indicate the confidence of an interval of 95%.However, [121] has the widest confidence interval compared to the GA or the H-FLGA, which indicates, these is likely to be more variation in the delay estimated using the [121] and the GA. Our results show that when ω_2 is set to 1 and solved only with GA, the maximum value of delay is $0.113s$ and the maximum value of delay when calculated using [121] is $0.171s$. However, the value of delay is lowered and improved to $0.062s$ when delay is computed using our proposed H-FLGA approach.



(a) Optimum number of Connections using Min-BBUC

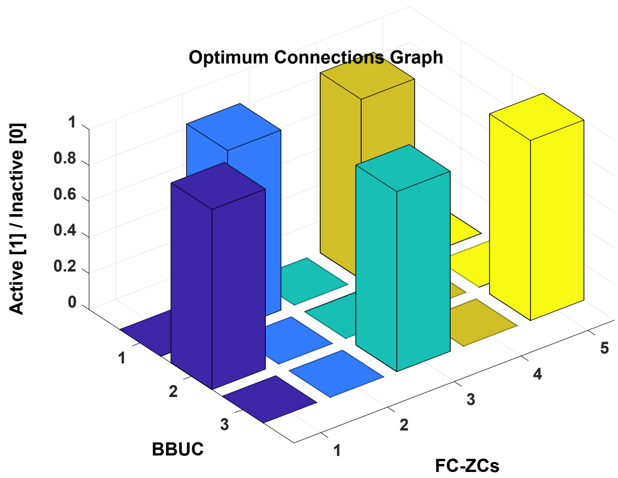


(b) Capacity Utilization of BBUC using Min-BBUC

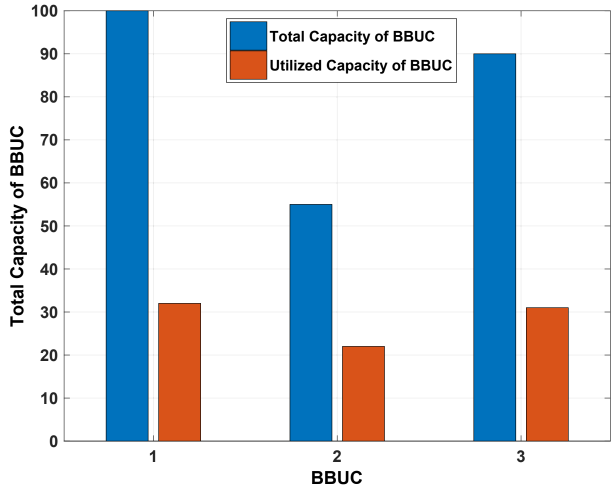


(c) Capacity Demands of FC-ZCs using Min-BBUC

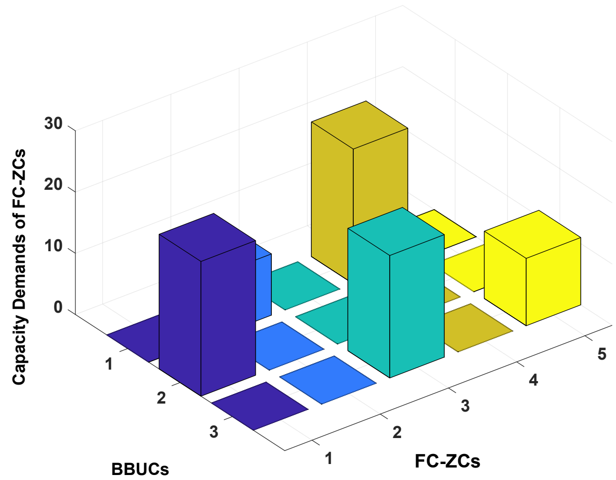
Figure 5.8



(a) Optimum number of Connections using Cap-LB

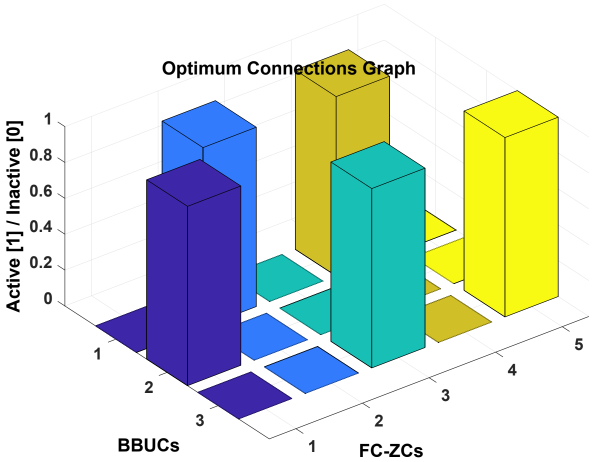


(b) Capacity Utilization of BBUC using Cap-LB

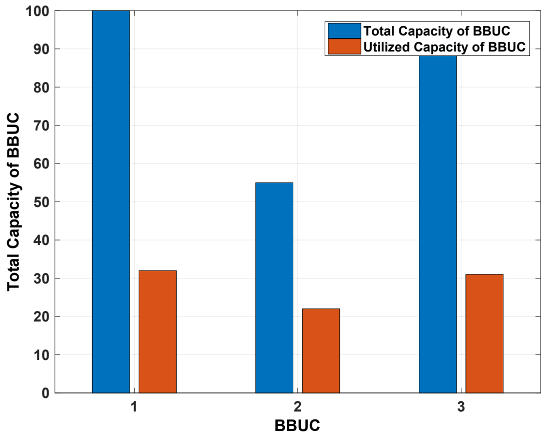


(c) Capacity Demands of FC-ZCs using Cap-LB

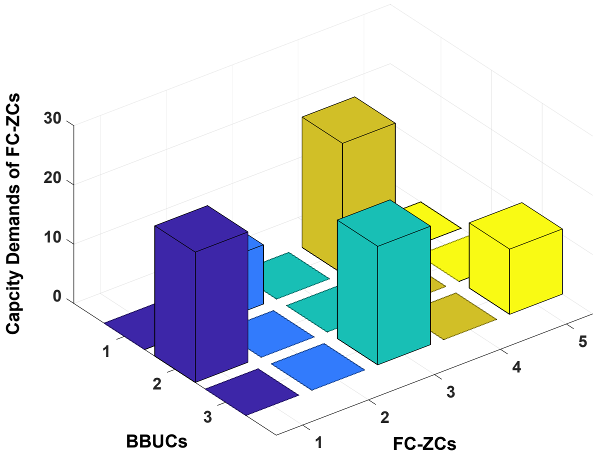
Figure 5.9



(a) Optimum number of Connections using FC-ZC-per-BBUC-Bal



(b) Capacity Utilization of BBUC using FC-ZC-per-BBUC-Bal



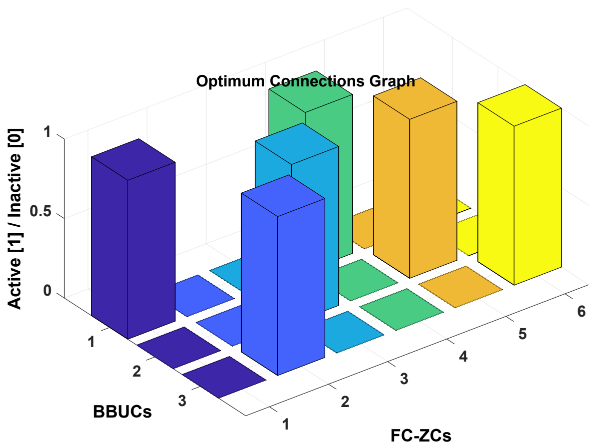
(c) Capacity Demands of FC-ZCs using FC-ZC-per-BBUC-Bal

Figure 5.10

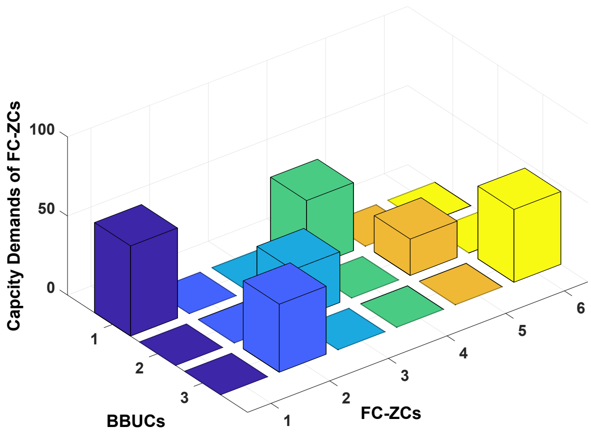
5.7 Conclusion

In this chapter, a hybrid Fuzzy Logic guided Genetic Algorithm (H-FLGA) approach is proposed for the SDN controller, for an optimum resource allocation for our proposed 5G-driven VANET architecture in Chapter 3.

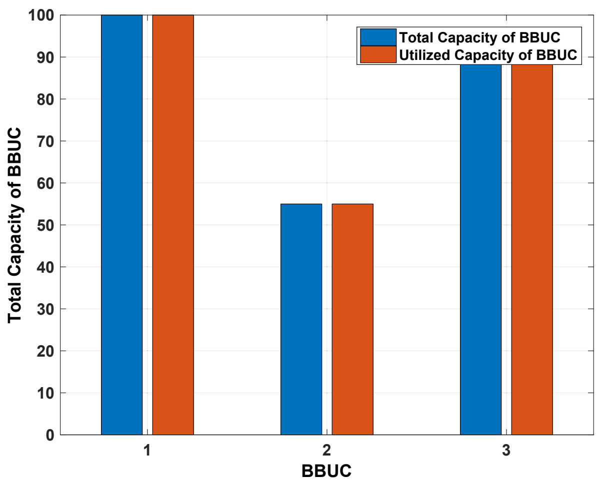
A multi-objective optimization problem is solved, where different objectives are combined and proposed FIS is used to optimize the weights of multiple objectives. These optimized weights are then used by the Genetic Algorithm to optimize connections between BBUCs and FC-ZCs. This work will help service providers to improve their spectral efficiency, where the network can automatically adapt to dynamic customer



(a) Optimum number of Connections using CTL

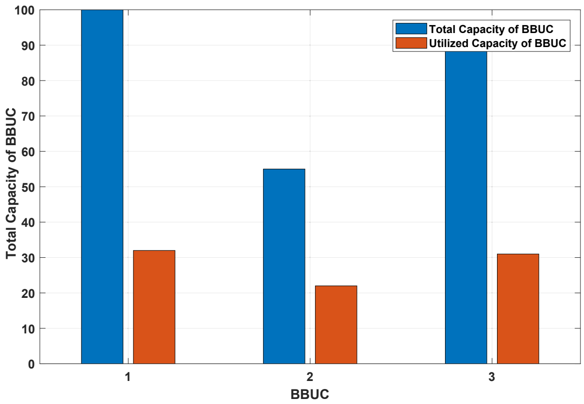


(b) Capacity Demands of FC-ZCs using CTL

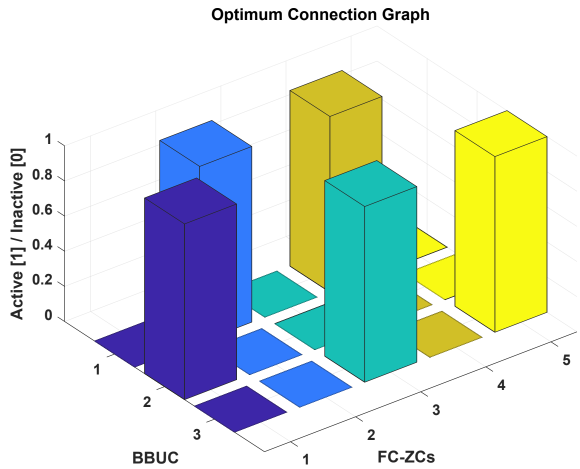


(c) Capacity Utilization of BBUC using CTL

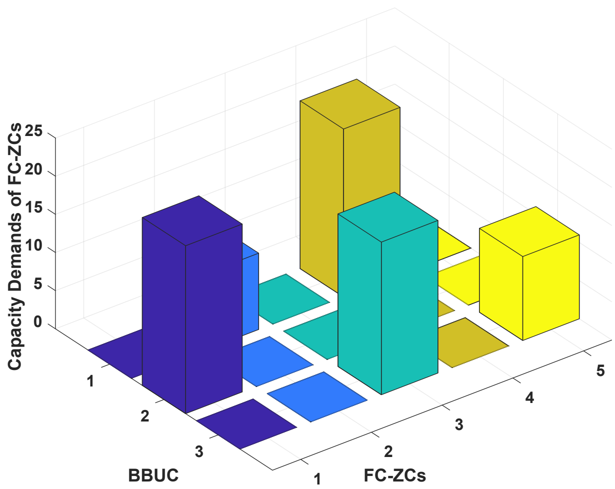
Figure 5.11



(a) Capacity Utilization of BBUC using H-FLGA



(b) Optimum number of connections using H-FLGA



(c) Capacity Demands of FC-ZCs using H-FLGA

Figure 5.12: Multi objective Optimization using Optimized weights

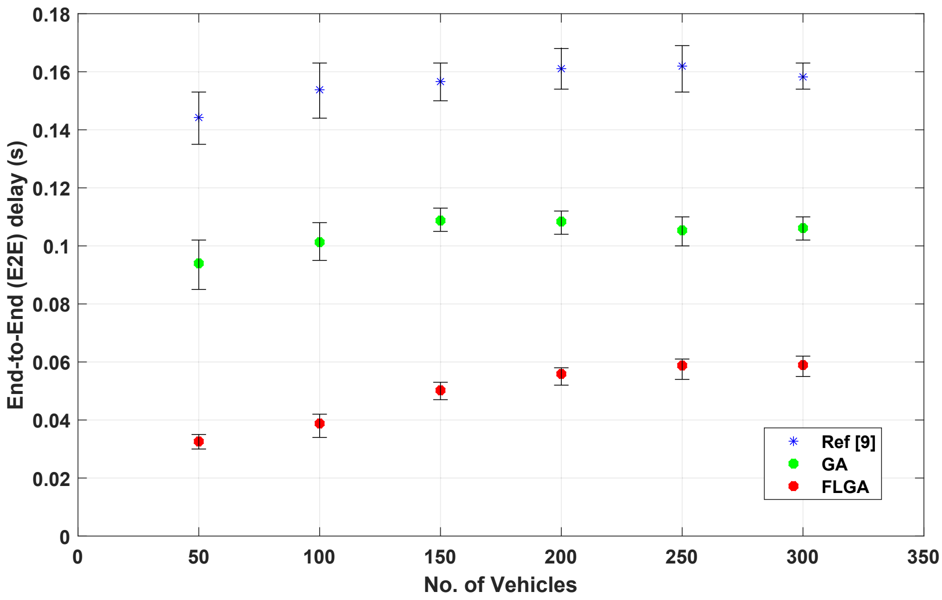


Figure 5.13: End-to-End Delay

Table 5.3: Simulation Parameters

Simulation Parameter	**Value**
Maximum capacity of BBUC pool	$100MHz$
Maximum Fronthaul distance	$40KM$
Number of Vehicles	50 *to* 300
Transmission range of vehicles	up to $300m$
Speed of Vehicles	between $10m/s$ and $30m/s$
MAC protocol	IEEE 802.11($11Mbps$)
Mobility Model	Manhattan grid ($2500m \times 2500m$)
Packet size	$512bytes$
Population size	2000
Tolerance for objective function	$1e-8$
Crossover Operator	single (or multi) point

needs and capacity demand fluctuations of users in VANETs, being cost-effective to operators.

It is concluded from the simulation results that the value of the multi-objective cost function is minimized using H-FLGA when compared with GA. It is also observed that the proposed H-FLGA approach minimizes End-to-End delay as compared to the GA and the 5G driven VANET architecture.

Chapter 6

An End-to-End (E2E) Network Slicing Framework for 5G Vehicular Ad-hoc Networks

6.1 Introduction

To accommodate high volumes of mission critical traffic, reserving radio resources may lead to over-provisioning of resources [15]. There is a need to define resource allocation strategies based on on-demand and instant allocations of resources. [16]. Network slicing is considered to be the key enabler to achieve high utilization of both communication and computing resources and minimize the infrastructure deployment cost [17]. Network slicing is expected to emerge as a promising solution for end-to-end resource management and orchestration together with Software Defined Networking (SDN) and Network Function Virtualization (NFV) technologies.
In this chapter, an E2E network slicing framework is presented with the consideration of both the radio access network resources and the core network resources in 5G-driven VANETs.
The following are major contributions of this chapter.

1. A comprehensive network slicing framework is presented to achieve end-to-end (E2E) QoS provisioning among customized services in 5G-driven VANETs,

with the consideration of managing the cooperation of both RAN and Core Network (CN) using SDN, NFV and Edge Computing technologies.

2. Furthermore, a dynamic radio resource slice optimization scheme is formulated mathematically, which handles a mixture of both best-effort traffic and mission-critical traffic, by keeping in view resource elasticity requirements

3. The solution adjusts the optimal bandwidth slicing and dynamically adapts to instantaneous network load conditions such that a targeted performance is guaranteed.

4. The problem is solved using a Genetic Algorithm (GA) and results are compared with our previously proposed 5G VANET architecture in chapter 3. Simulations results reveal that the proposed slicing framework is able to optimize resources and deliver the targeted KPIs of mission critical demands.

The remainder of the chapter is organized as follows: Section 6.2 provides some background on network slicing in 5G architecture. Section 6.3 describes network slicing framework section 6.4 explains problem formulation. Section 6.5 provides results and discussions and finally, Section 6.6 concludes the chapter.

6.2 Background and Related Work

The era of the fifth generation (5G) cellular networks is rapidly evolving. 5G networks are anticipated to support a number of vertical industries that are characterized by diversified use cases and applications. Some of the most popular use-cases are Intelligent Transportation Systems, Mobile Broadband, Massive number of Internet-of-Things (IoT), Mission-critical IoT, and e-health care systems, all require diverging features and performance requirements in terms of latency, reliability, security and policy control [143], [144]. A key emerging use case of intelligent transportation is handling mission-critical traffic in 5G vehicular networks. Considering the features of mission-critical traffic, not only the precise and timely delivery of information is required, but also other stringent key performance Indicators (KPIs) such as ultra-reliability and low latency communications need to be achieved [145]. The concept of network slicing has been thoroughly studied in different domains [146]- [147]. In the SDN-enabled environments using NFV, virtual network functions (VNFs) (decoupled from the physical network infrastructure) are instantiated and are placed on NFV nodes. In the core network, physical resources are abstracted and are allocated to different Virtual Machines (VMs) hosting VNFs thorough virtualization layer. These VNFs are programmable commodity servers running VMs and are flexibility orchestrated to provide differentiated E2E services. Furthermore, to ensure reliable and timely delivery of mission-critical traffic over RAN alone is not sufficient to guarantee the required end to-end reliability, since the Core Network (CN) part has to also be considered. Particularly, the transport network plays an important role in the successful delivery of KPIs, such as reliability. Both mission-critical and best-effort traffic will have to travel through a complex network while competing for resources during transmission, buffering, and computing. Moreover, Mobile Edge Computing (MEC) technology is also introduced by the ETSI ISG on MEC [148], that offers cloud-computing capabilities within the Radio access network and an information technology service environment closer to end user devices or edge. MEC environment offers benefits of ultra low latency, high bandwidth utilization, and real-time access to RAN information that can be used by differentiated services or applications and QoS optimization platforms. To achieve E2E QoS isolation among different traffic flows, the set of network resources including computing resources on NFV nodes and bandwidth resources on transmission links must be carefully isolated [17]. This can be achieved by using the concept of network slicing. A network slice is a collection of Core Network (CN) and Radio Access Network (RAN) functionalities, configured to meet the diverse service requirements in terms of functionalities (i.e., mobility, support and security) and delivery performance (i.e., throughput, reliability and latency) [149]. CN Network slicing is interpreted as bi-resource slicing [150]. Whereas, RAN slicing mainly deals with how to slice the overall radio resources. In RAN slicing, the radio access functions on each Base Station are softwarized and are centrally managed by the SDN enabled virtualization controller. The SDN controller determines the amount of radio resources to be allocated to each BS to enhance the overall spectrum utilization. Existing studies presents network slicing solutions for 5G network domains across Vehicle-to-everything V2X [146], RAN segments [151]- [152] and CN segments [153].

Most of the studied issues related to network slicing are currently under investigation and particularly limited research focuses on determining the sets of resources for customized services, to achieve a desired trade-off between high resource utilization and end-to-end QoS isolation by considering heterogeneous resources. However, to the best of our knowledge, this is the first time the concept of network slicing is studied to achieve end-to-end QoS provisioning among customised services in 5G Vehicular Ad-hoc Networks.

6.2.1 Network Slicing in 5G Architecture

With the evolution of 5G technology, network slicing has emerged as a major new networking paradigm, to support a wide range of verticals with a diverse set of performance and service requirements. Different network operators and vendors are all recognizing it as an ideal network architecture for the upcoming 5G era [18]. Network slicing allows network operators to create multiple virtual end-to-end (E2E) logical networks running on a common underlying physical or virtual network infrastructure [143], [144], [154], [155]. Each slice is logically isolated including network device, radio access, transport and Core Network (CN), and dedicated for different types of services with different characteristics and requirements. These slices can be created on demand with independent control and management [156]. Technologies like Software Defined Networking (SDN) and Network Function Virtualization (NFV) are used to tailor the network for a given use case, and create multiple logical networks on the top of a common physical or virtual network infrastructure [153]. For each network slice, dedicated resources such as bandwidth storage, processing or Traffic are sliced and virtualized network functions (VNFs) are placed in different locations (i.e., Edge Cloud or CN Cloud) for each slice depending on different service requirements. Also different slices are isolated, which means an error or a fault occurred in one slice does not cause any service interruption on overall communication in other slices. Depending on the type of service requirements of different use cases (e.g., Mobile Broadband, Massive IoT, and Mission-critical IoT), each slice is isolated to meet certain QoS acquirements, such as Low latency and ultra reliability. QoS isolation guarantees that the minimum level of QoS experienced by end users or devices belonging to one type of service is not despoiled on change in network state such as, mobility and traffic load fluctuation, at another service type. Network slicing can provide more cost effective solutions for Intelligent transportation systems (ITS) by offering multiple logical networks over a single physical network, instead of creating dedicated networks for each single service such as, one for autonomous driving, one for road safety, another for 5G mission-critical applications. In 5G, latency critical services demand an E2E delay between 1 ms to 100 ms [157]. The network slicing solution involves the partition of the Core Network (CN) and the Radio Access Network (RAN) resources including the configuration of the end-device vehicle functionality, to support different use cases [146]. Cloud-RAN (C-RAN) technology plays an important role to attain the on-demand deployment of RAN functionalities. Using C-RAN the radio and the baseband processing functionalities are segregated. While the base band functionalities are migrated towards the cloud and form a BBU pool and are controlled centrally. The centralized processing of the BBU pool functionalities saves time (i.e., processing and signalling time) for handovers as compared to a distributed processing at each eNodeB. By leveraging the concept of virtualization technologies, C-RAN resources in the pool can be dynamically allocated to eNode Base stations according to the load on network. This ensures adaptability to the non-uniform vehicular traffic scenarios during off-peak/rush hours, in urban or rural environments. In the core network, SDN and NFV have been introduced to support large capacity and low latency and massive connectivity with seamless procedures. Since these technologies are not part of the legacy LTE system, extensive research is being carried out for the development in the context of 5G networks. The main challenge of SDN/NFV-based core network design is the management and orchestration of heterogeneous resources [158]. Implementation of effective resource allocation strategies and functions in heterogeneous environment while also maintaining low latency is an area of emerging research. Network slicing in wireless domain (RAN slicing) mainly deals with how to slice the overall radio resources for different device groups to ensure QoS isolation. The radio access functions on each BS are softwareized and are centrally controlled and managed by the SDN enabled virtualization controller. Whereas, in the core network, network slicing is interpreted as bi-resource slicing. The SDN controller can determine the amount of radio resources allocated to each Base station to improve the overall spectrum utilization. As the 5G architecture is still evolving, the existing research present new architectures for network slicing in different domains like wireless or a core network [151], [152], [153]. However, limited research focus on presenting radio resource slice optimization schemes in 5G-driven VANETs.

In this study an E2E network slicing framework is constructed that handles a mixture of best-effort traffic from regular users and mission-critical traffic from the prioritized user in 5G -driven VANETs. Moreover, a dynamic radio resource slice optimization scheme is presented in the context of E2E reliability of critical traffic at the softwareized 5G CN level. The network is configured to always guarantee requested data rate for the mission-critical traffic, even if it leads to deteriorating the QoS of the best-effort sessions for regular users. Both the best-effort and the mission-critical traffic will have to travel through a complex network including RAN and CN to compete for radio resources during transmission.

6.3 End-to-End Network Slicing framework in 5G-driven VANETs

A detailed practical framework is constructed for the end-to-end network slicing in 5G-driven VANETs, by leveraging the concepts of NFV, SDN, C-RAN and Edge Computing technologies as shown in Figure. 6.1. The proposed solution handles a mixture of best-effort traffic from regular users and mission-critical traffic from the prioritized user and, performs slicing by keeping in view both the RAN and the CN as shown in Figure. 6.2.

6.3.1 Hierarchy/levels of slicing for proposed E2E slicing framework:

To have a closer look at how E2E network slices are actually implemented, we discuss slicing at different levels or hierarchies such as ***Edge Cloud (EC)*** and ***CN Cloud*** with respect to proposed framework shown in Figure. 6.2. Dedicated slices are created for services with different requirements and Virtualized Network Functions (VNFs) are placed in different locations (i.e., EC or CN cloud) for each

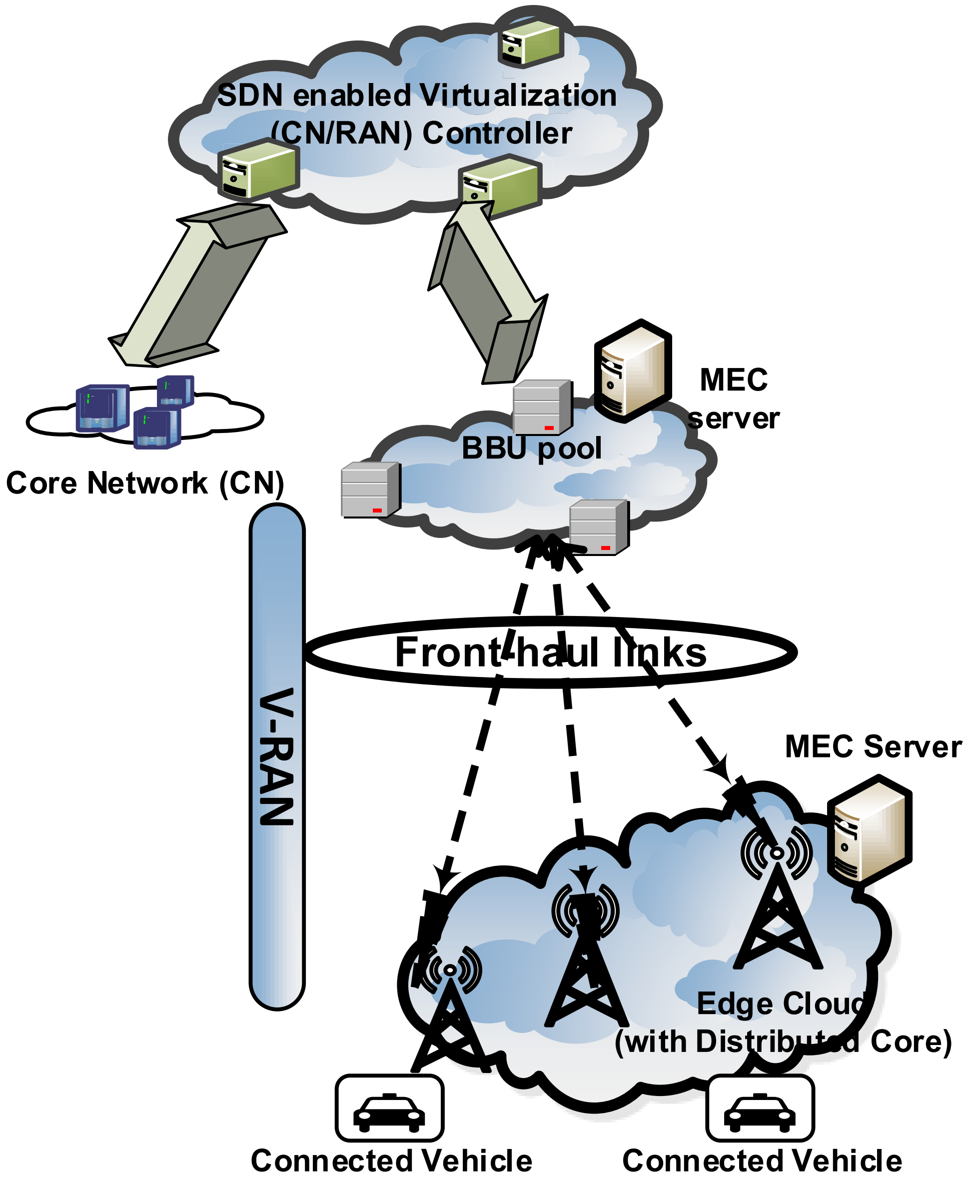


Figure 6.1: An End-to-End (E2E) Network Slicing Framework for 5G-driven VANETs

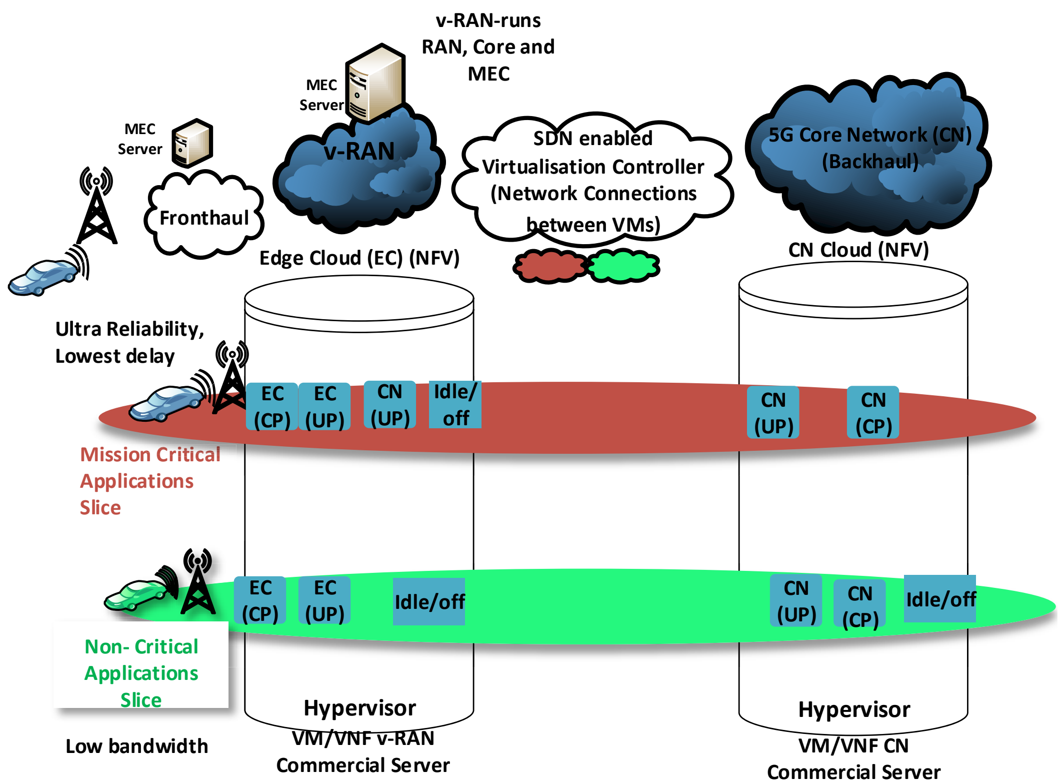


Figure 6.2: E2E mission critical slicing including CN and RAN in 5G-VANETs

slice depending on services. Moreover, some network functions, like policy control, charging, and etc., required in one slice may not be compulsory in other slices. The proposed framework will allow the network operators to customize slices based on different service requirements, in the most cost-effective way by placing VNFs at different locations using NFV, and by having a separate Control plane (CP) and user plane (UP) using SDN. The proposed framework is hybrid and flexible where processing is centralized for some services and distributed for others. Let's have a closer look at the levels of slicing and how slices are implemented.

6.3.2 Edge Cloud (EC) and CN Cloud:

EC distributes 5G Core Network (CN) close to cell sites or end-users or edge. Edge may refer to the base stations/Remote Radio Heads (RRHs), Connected vehicles and data centres close to the radio network (e.g., located at aggregation points). **Virtualized RAN** (v-RAN) runs RAN, Core and MEC operations. Operators can operate **v-RAN** by deploying innovative applications and services for different enterprises and verticals, flexibly and rapidly. Since, there are different slice isolation requirements that consider specific resource management means to meet various KPIs. Each slice may need a different control plane (CP) and User plane (UP) functional split, and a distinct VNF placement (at either EC or CN cloud) to ensure an optimal performance.

How to implement network slices on EC and CN Cloud

To implement network slices, Network Function Virtualization (NFV) is a basic requirement. Using NFV, Virtual Network Functions (VNFs) (e.g., MME, S/P-GW and PCRF in Packet Core, and DU in RAN) are installed on to Virtual Machines (VMs). Such VMs are deployed on a virtualized commercial server usually known as *Commercial off-the-shelf (COTS)*, instead of installing on to their dedicated network equipment individually. According to Figure. 6.2, applications dedicated for each service (i.e., mission critical and non-critical) are virtualized and installed in each slice. The VNFs are placed at different locations i.e., EC or CN Cloud depending on the service requirements. In short, slices can be configured as follows.

Mission-critical slice To meet Key Performance Indicators (KPIs) for ***mission critical application slice*** (i.e., ultra reliably and lowest latency communication), the VMs of 5G ***CN*** (User plane (UP) and Control Pane (CP)) and associated servers (e.g., V2X server, MEC server and etc.,) are all down in Edge Cloud (EC). Slice allocation is performed on demand to meet ultra reliability and minimized transmission delay.

Non-critical slice On the other hand, ***non-critical application slice*** is based on best-effort allocation of resources. The VMs of 5G ***CN*** (User plane (UP) and Control Plane (CP)) will remain on CN cloud. However, some functionalities that are required to be processed by end user devices or vehicles, will be handled by VMs of User plane (UP) and Control Pane (CP) placed at EC.

Network slicing between EC and CN cloud

The SDN-enabled virtualization controller performs ***VM (VNF) Creation and Control at EC and CN Cloud*** and ***provides network connectivity between VMs in Edge and Core clouds***. Traffic Flows for different types of services, (aggregated through back-haul links) are automated by SDN controller. In order to maintain the priority of the mission critical flows with respect to other flows (e.g., best-effort traffic), the SDN controller maps the flows onto a priority queue. The SDN controller takes the chain of services and apply them to different traffic flows depending on the source, destination or type of traffic. This Service function chaining (SFC) capability of SDN controller creates a service chain of connected network services (such as, firewalls, DNS, network address translation (NAT), Intrusion Detection System (IDS)), and connect them in a virtual chain [150]. Using SFC embedding, SFCs can be placed on VNF nodes at various locations along the paths from CN to EC. SDN Controller also performs provisioning of the virtualized server (built-in vRouter/vSwitch running in Hypervisor of the server).

The complete E2E process of slicing between CN and EC cloud can be illustrated from Figure. 6.3. 1. SDN Controller receives two incoming traffic flows from end user application requests (i.e., FL_1 for Mission Critical (MC Flow) and FL_2 for non-Mission Critical (non-MC Flow). Each flow requires different VNFs and logic SFCs. Using SFC embedding, these logic SFCs will traverse one embedded underlay path to fulfil the required KPI's. 2. For each flow, Controller creates the VNF on demand (i.e., V_{FL_1} for MC slice and V_{FL_2} for non-CR slice). The Packets of flow FL_1 and FL_2 will go through the VNFs (F_{FL_1} and F_{FL_2}) on NFV nodes (V_{EC} and V_{CN}) for processing. These packets will then be transmitted by a set of outgoing underlay transmission links $\{L_0, L_1, L_2, ..., L_m\}$ and network routers $\{R_1, R2, ..., R_l\}$ before arriving at destination. 3. For each slice, an overlay tunnel is created. Connecting slicing from Edge cloud, to IP/MPLS backbone, and all the way to Core Cloud. The SDN Controller performs mapping between these tunnels and MPLS L3 VPN (e.g., MC slice VPN and non-CR slice VPN). This process will be implemented using current available technologies and standards (e.g., (L2/L3 VPN, VXLAN, OTV, LISP and etc.).

6.4 Problem Formulation

A multi-objective solution, that handles a mixture of best-effort traffic and mission-critical traffic, by considering capacity allocation per slice and minimising delay is

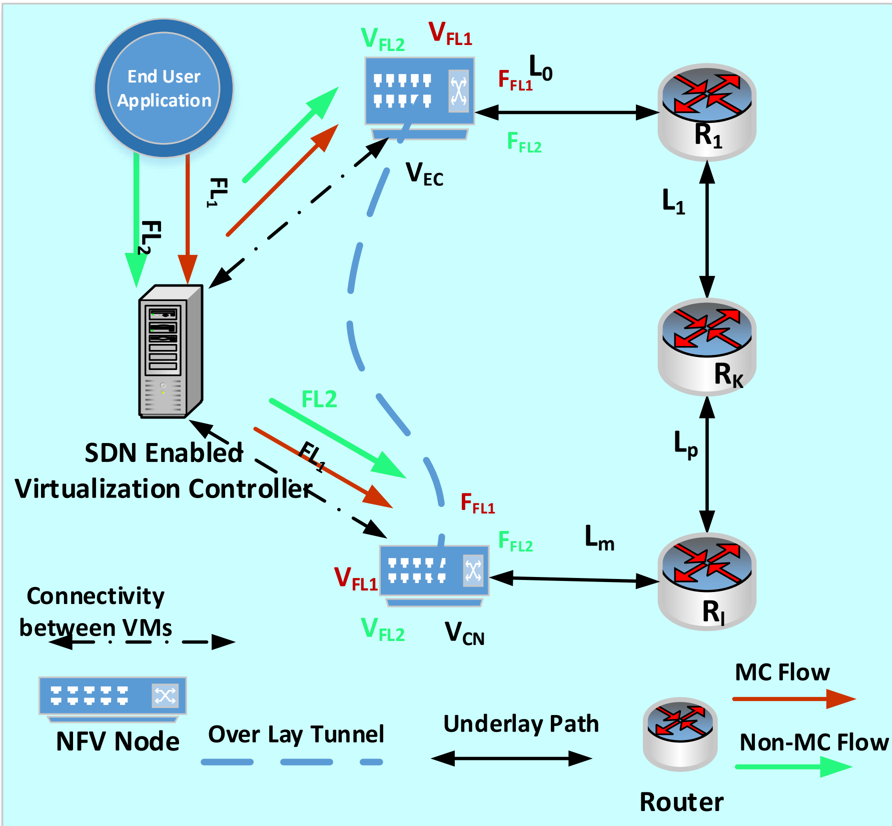


Figure 6.3: E2E Network Slicing Between EC and CN Cloud

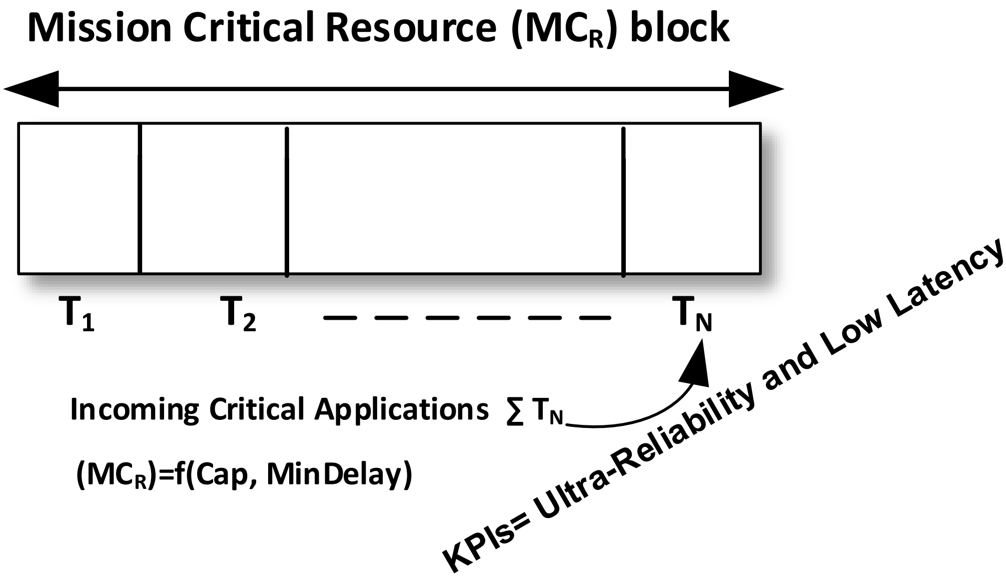


Figure 6.4: Mission Critical Resource Block

proposed. The overall bandwidth resources are sliced in C-RAN, for mission critical applications and non-critical applications, by keeping in view resource elasticity requirements. To implement the concept of slicing for mission critical and non-critical traffic, we formulate the problem as follows.

Let $RRH = \{RRH_1, RRH_2, ..., RRH_n\}$ with cardinality $|RRH| = n_{RRH}$ represents the set of Remote Radio Heads or Base stations that are distributed in an area and n_{BBUC} represents number of BBU Controllers (BBUC).

Let $BBUC = \{BBUC_1, BBUC_2, ..., BBUC_n\}$ with cardinality $|BBUC| = n_{BBUC}$ represent the set of BBUCs, such that $n_{BBUC} \leq n_{RRH}$. Let $Links = \{BBUC_i, RRH_j\}$ represents the set of possible link pairs between BBUCs and RRHs.

Variables

$$Z_{ij} = \begin{cases} 1, & if \quad RRH_j \quad is \quad served \quad by \quad BBUC_i \\ 0, & otherwise \\ where(i,j) \in Links \end{cases}$$

$$Y_i = \begin{cases} 1, & if \quad BBUC_i \quad is \quad Chosen \\ 0, & otherwise \end{cases}$$

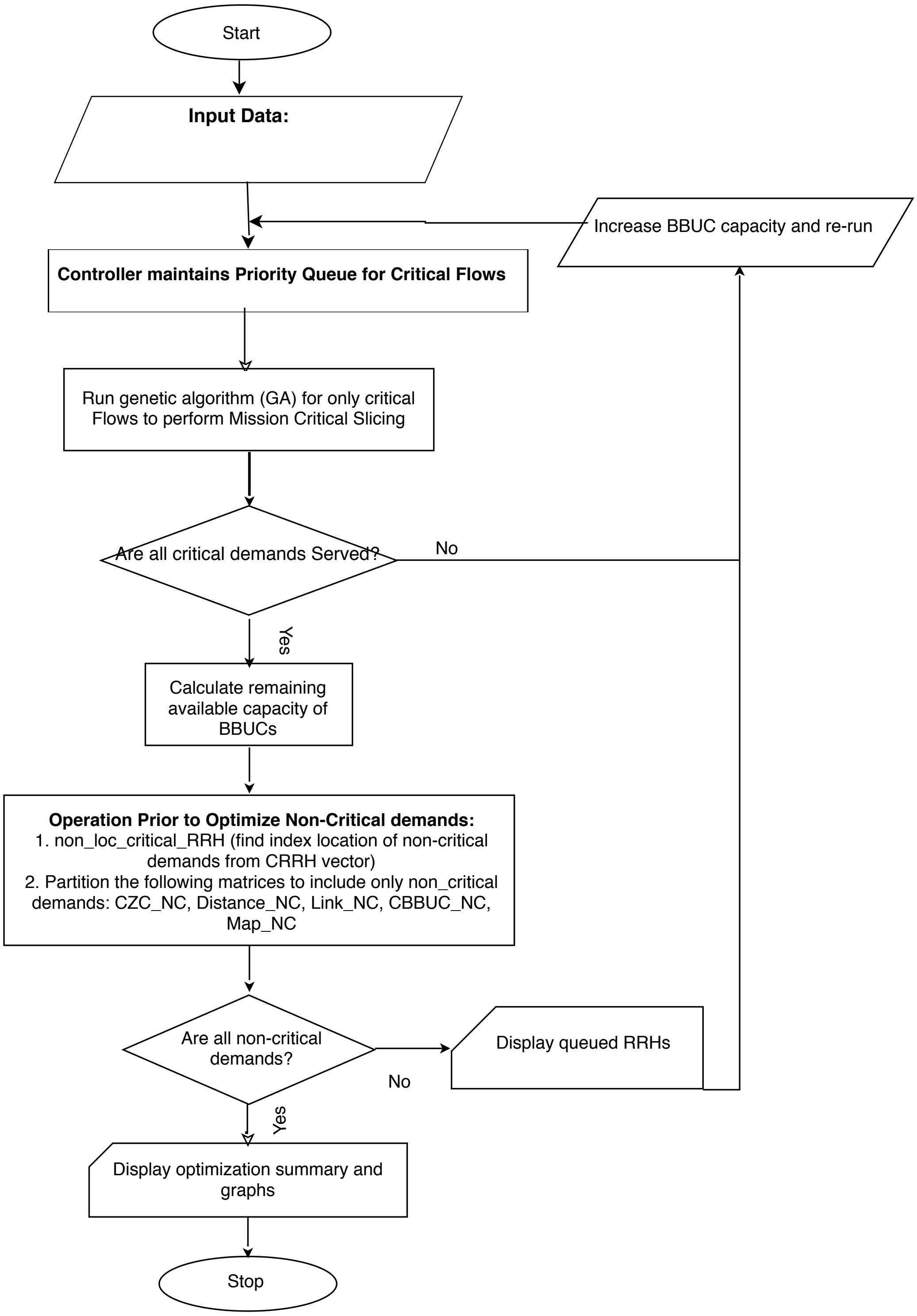


Figure 6.5: Program Flow Chart of Proposed E2E slicing Scheme

6.4.1 Objective function

To deal with mission-critical application, there is a need to meet certain QoS requirements such as ultra-reliability and low Latency. Hence, the KPIs for mission critical slice are ultra-reliability (guaranteed service) and low latency (minimised delay) as shown in Figure. 6.4. The main objective function for mission Critical Resource Block C_{MC_R} is given as

$$C_{MC_R} = \sqrt{{min_{delay}}^2 + {Cap_{utl}}^2} \tag{6.1}$$

The individual objective functions for capacity utilisation and minimised delay are discussed as follows.

Capacity Utilisation(Cap-utl)

To provide guaranteed delivery for mission critical demands, we allocate resources by balancing the load on each BBUC. For this we propose the Cap-utl algorithm that aims to balance the critical demand load in every BBUC Pool. The information of critical demand load of each BBUC Pool is always available and updated by the SDN controller. Before evaluating the decision, the controller has the information of traffic load of the possible BBUC Pool connections, thus, the controller will check not only the maximum capacity limit of the BBUC Pool, but also maintain the priority queue for mission critical demands. The objective function is given by

$$\text{Minimize } Cap_{utl} = \frac{1}{n_{BBUC}} \sqrt{\sum_{i=1}^{n_{BBUC}} (D - D_i)^2} \tag{6.2}$$

where $D_i = \sum_{j=1}^{n_{RRH}} Z_{ij} C_{RRH_j}$ is i^{th} element indicating the total critical demand in BBUCi in the total load demand vector D and $D = \frac{1}{n_{BBUC}} \sum_{i=1}^{n_{BBUC}} D_i$ is the average demands across all BBUCs. The idea behind the objective function is to reduce the standard deviations of the total load demand vector D. Under ideal conditions, if the capacity demand is the same in all BBUCs, the positive objective function value must be equal to zero.

Minimise Delay

The objective of this problem is to minimize the front-haul delay by connecting RRHs closer to the possible BBUC Pool location. The SDN controller has all the possible locations of BBUC Pools, thus, knowing all the distances between possible link connections between RRHS and BBUCs. Since, delay is considered to be directly proportional to the front-haul distance between RRHs and BBUCs which in turn is related to the cost associated with linking BBUC and RRHs. Hence the objective function is given by

$$min_{Delay} = \sum_{i=1}^{n_{BBUC}} \sum_{j=1}^{n_{RRH}} Cost_{i,j} Z_{ij} \tag{6.3}$$

where n_{BBUC} is the number of BBUCs in the pool, $Cost_{i,j}$ is the front-haul link cost for linking RRHs j and $BBUC_i$ in the cost matrix $Cost$. Equation 6.2 and 6.3 are subject to the following constraints;

1. Sum of demands of RRHs connected to BBUC i must be less than or equal to available link capacity of that BBUC i.

   $$\sum_{j=1}^{n_{RRH}} Z_{ij} C_{RRH_j} \leq C_{BBUC_i} \tag{6.4}$$

   where $j\epsilon\{1, 2, ..., n_{RRH}\}$ and $i\epsilon\{1, 2, ..., n_{BBUC}\}$. C_{RRH_j} is j^{th} element with a value equal to the critical/non-critical capacity demands of RRH j in capacity demand row vector C_{RRH}.

2. BBUC i should be serving if atleast one RRH is connected to it.

   $$Z_{ij} \leq Y_i \tag{6.5}$$

   where $j\epsilon\{1, 2, ..., n_{RRH}\}$ and $i\epsilon\{1, 2, ..., n_{BBUC}\}$.

3. BBUC i should not be serving if no RRHs are connected to it.

   $$\sum_{j=1}^{n_{RRH}} Z_{ij} \geq Y_i \tag{6.6}$$

   where $j\epsilon\{1, 2, ..., n_{RRH}\}$ and $i\epsilon\{1, 2, ..., n_{BBUC}\}$

6.5 Simulation results and Discussions

In this study, simulations are conducted to evaluate the performance of network slicing for proposed framework. MATLAB® is used to run the optimization of the

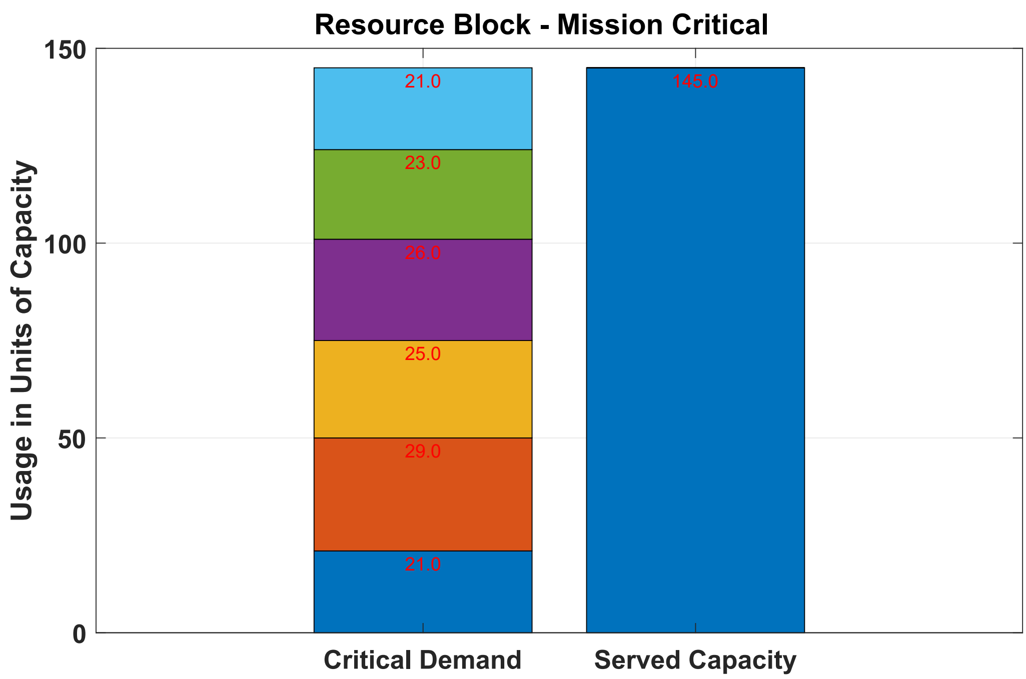


Figure 6.6: Optimum Utilization of resource for Mission Critical slice

objective function. Genetic algorithm (GA) is used for conducting optimization. The following settings for the GA parameters are chosen: population size of 2000, generation size of 100, elite rate of 5%, tolerance value of 1e-8. Figure. 6.5 shows the program flow of how it is executed. In the present problem, the GA is run two times: (1) for critical demands and (2) for non-critical demands on the remaining capacities available in different BBUCs. The maximum front-haul distances $d_{fronthaul}$ (that determines the radius of coverage of every BBU Pool) are set according to the two transmission technologies. Fibre link – maximum distance of 40 km and link propagation speed $v_{fronthaul}$ of 200 km/ms. Microwave link – maximum distance of 1.5 km and link propagation speed $v_{fronthaul}$ of 300 km/ms as taken in [159]. For the core network, we consider two flows, FL_1 and FL_2 representing two logic SFCs traversing one embedded overlay network path. We set different packet sizes for flow FL_1 and FL_2 at V_{EC} that depends on the service requirements (i.e. mission critical or non-mission critical). The proposed framework allows FL_1 and FL_2 that require different levels of QoS, to dynamically control their respective KPIs depending on the effective demands by each of these flows. To maintain the priority of the mission critical flows with respect to other non-mission critical flows (i.e. best-effort traffic), the SDN controller maps the flows onto a priority queue. In mission

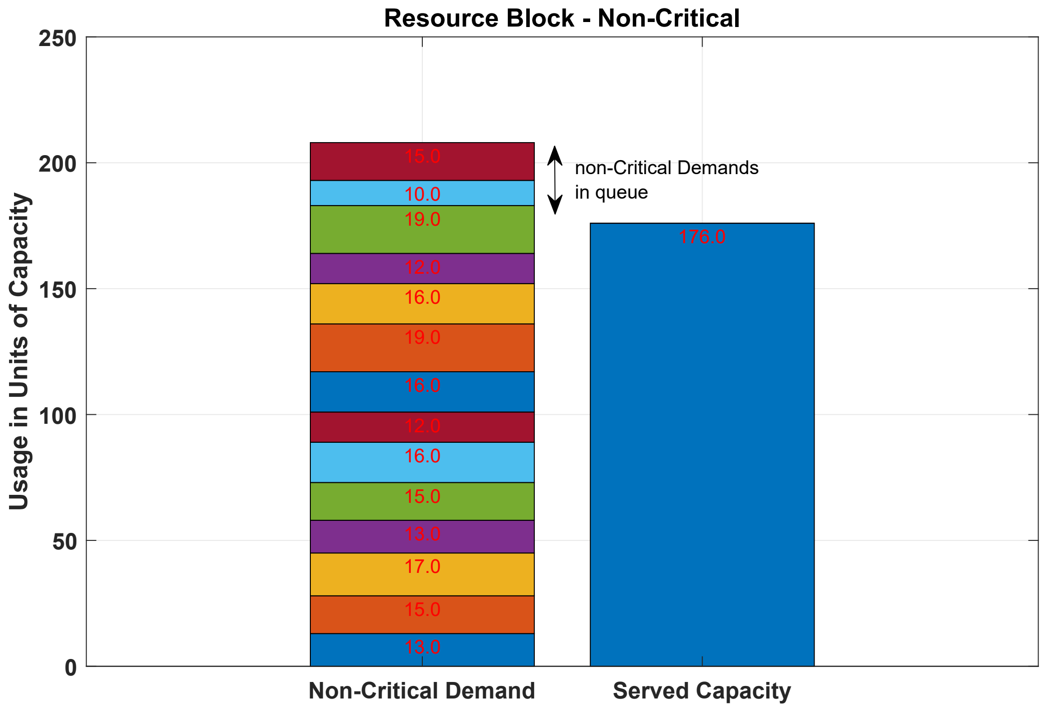


Figure 6.7: Optimum Utilization of resource for non-Critical slice

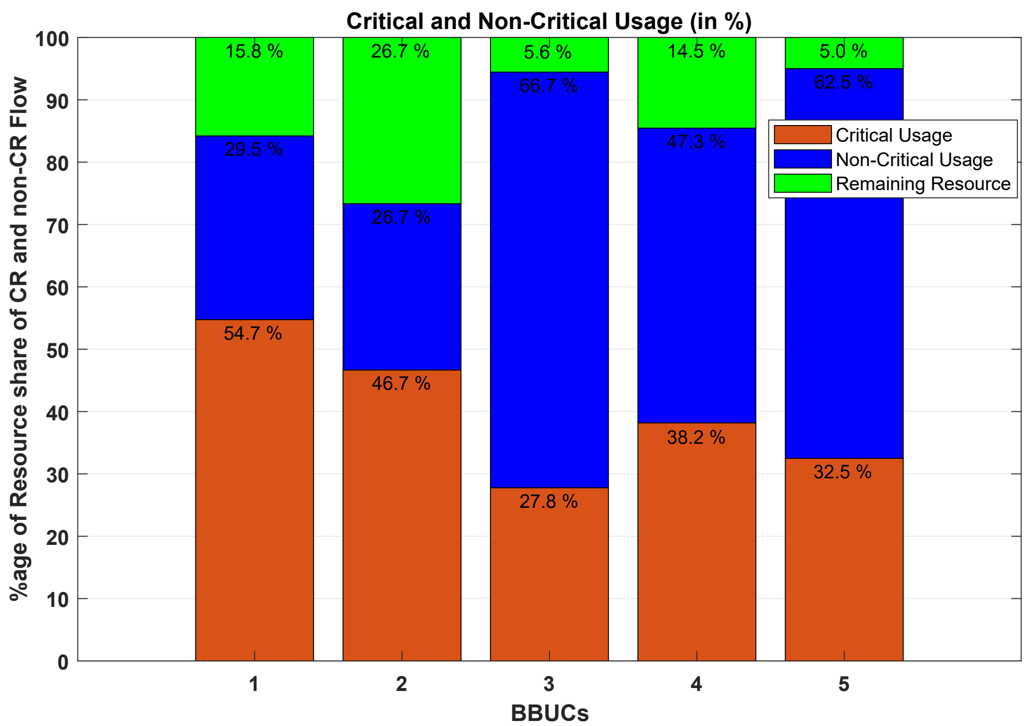


Figure 6.8: Combined resource utilization for both Critical and non-Critical slices

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OPTIMIZATION SUMMARY
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(*) All critical demands have been allocated

(*) Queued critical RRH(s): No critical RRH in queue

(*) Non-operating BBUC(s) after allocation of critical RRH(s) : All BBUC(s) engaged

(*) Remaining capacity in BBUCs after allocation of critical RRH(s) :
     BBUC 1: 43 (45.26%)
     BBUC 2: 24 (53.33%)
     BBUC 3: 65 (72.22%)
     BBUC 4: 34 (61.82%)
     BBUC 5: 54 (67.50%)

(*) Not all non-critical demands have been allocated. Please re-run GA or increase BBUC capacities

(*) Queued non-critical RRH(s):2, 4,

(*) Capacity requirements for non-critical queued RRH(s) :
     BBUC 2, Demand: 15  BBUC 4, Demand: 17
     Total requirement for non-critical = 32

(*) Non-operating BBUC(s) after allocation of non-critical RRH(s) : All BBUC(s) engaged

(*) Remaining capacity in BBUCs after allocation of non-critical RRH(s) :
     BBUC 1: 15 (15.79%)
     BBUC 2: 12 (26.67%)
     BBUC 3: 5 (5.56%)
     BBUC 4: 8 (14.55%)
     BBUC 5: 4 (5.00%)

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Figure 6.9: Optimization summary as output from MATLAB

critical communication, (ultra reliable low latency communication URLLC), both the latency and reliability issues are addressed. For investigating ultra reliability in mission critical communication, the objective function in equation 6.1 is solved using GA. All RRHs are allowed to connect with any of the BBUCs and its distance to each BBUC is calculated using equation 6.3. After running the program, the optimization summary is shown in Figure 6.9. Figure.6.10 shows the graph obtained from the GA run process. It shows the mean and best values in each generation. It is observed that as the optimization progresses the mean and best converges. This indicates that towards the end of optimization process, all the eligible solutions become closely the same. we see how to optimize slicing of radio resources at BBUC pool for mission critical traffic, using proposed objective functions in equations 6.2 and 6.3. To exploit resource multiplexing gain, the amount of resources of each slice is dynamically adjusted according to changes of network conditions. Our results in Figure. 6.6 illustrate that the mission critical resource block is dynamically adjusted as per the arrival of mission critical demands from end users/vehicles. The results

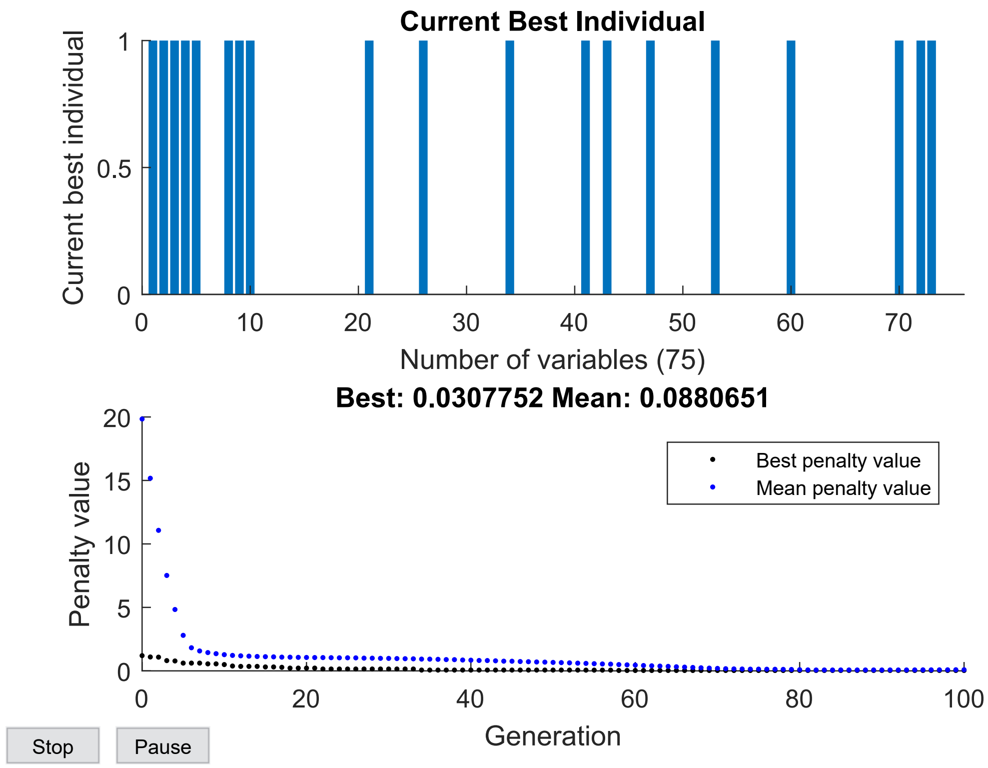

Figure 6.10: Optimization using GA

are tested on varying demands of mission critical requests and it is observed all the mission critical demand are served. The served capacity for mission critical slice is flexible and is dynamically adjusted with reliability as high as 99.99%. Hence our results prove that the proposed objective meet ultra reliability for mission critical communications. On the other hand, non-mission critical demands are served on best effort delivery and are not prioritized, hence few non-critical applications will be in queue as illustrated in Figure. 6.7. This is because the controller maintains a priority queue of critical applications. Figure. 6.8 shows resource utilization for each BBUC after the allocation for both critical and non-critical resource slices. Each bar represents various types of usages in each BBUC. We observed that BBUC 1 has the maximum critical allocation with 54.7% while BBUC 3 has the maximum non-critical allocation at 66.7%. It also displays the remaining capacities. Figure. 6.11 shows the distance of each RRH to the actively connected BBUCs. Ideally, these distances will be least possible distances to connect after the optimization. It is observed that RRH 19 and 20 are the farthest RRHs being served with 8 km of front-haul distance. Figure 6.12 shows the optimum active connections of

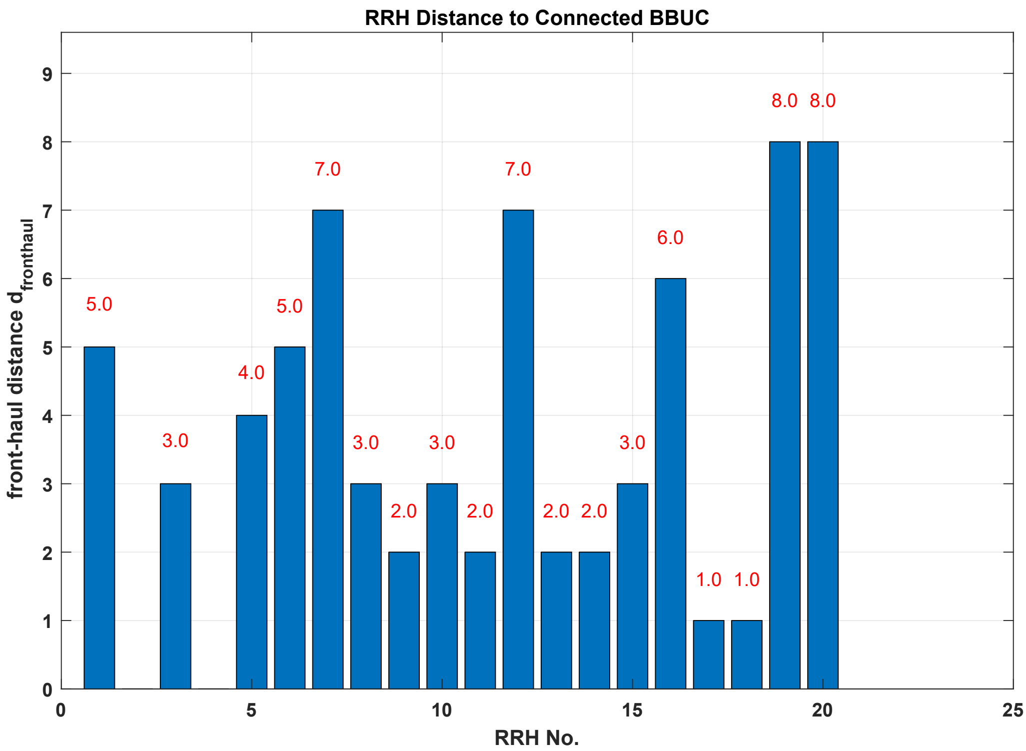

Figure 6.11: Optimized Front-haul distances of RRHs with BBUCs using equation 6.3

RRH with BBUCs. 1 and 0 indicates active and inactive connections. To analyse E2E latency of mission critical slice, we first determine the length of front-haul link between RRH and BBUC which is calculated using equation 6.3. It is important to note that latency is represented by the measure of Round Trip Time (RTT), which has a more meaningful impact on Quality of Experience (QoE) than One-Way Delay (OWD). For simplicity, the RTT δ_{RTT} is calculated using $2 * \tau_{OWD}$, where $\tau_{OWD}(ms)$ is one way delay [159]. The length of the front-haul link $d_{fronhaul(km)}$ is described by transmission speed $\upsilon_{fronthaul(km/ms)}$ of front-haul link and by the front-haul one way delay τ_{OWD}. We compare results of E2E latency at different link propagation velocities with previously proposed 5G VANET architecture [9]. Figure 6.13 shows the maximum E2E front-haul latency at each RRH for mission critical slice. This is based on taking the different propagation velocities both in fibre and in microwave links into account. As expected from the previous discussion regarding distance, the E2E delay will be maximum for RRH 19 and 20 due to maximum front-haul distance for our proposed slicing framework. Figure 6.13 illustrates that maximum E2E latency on RRH 19 and 20 (that are at farthest distance from BBUCs) is

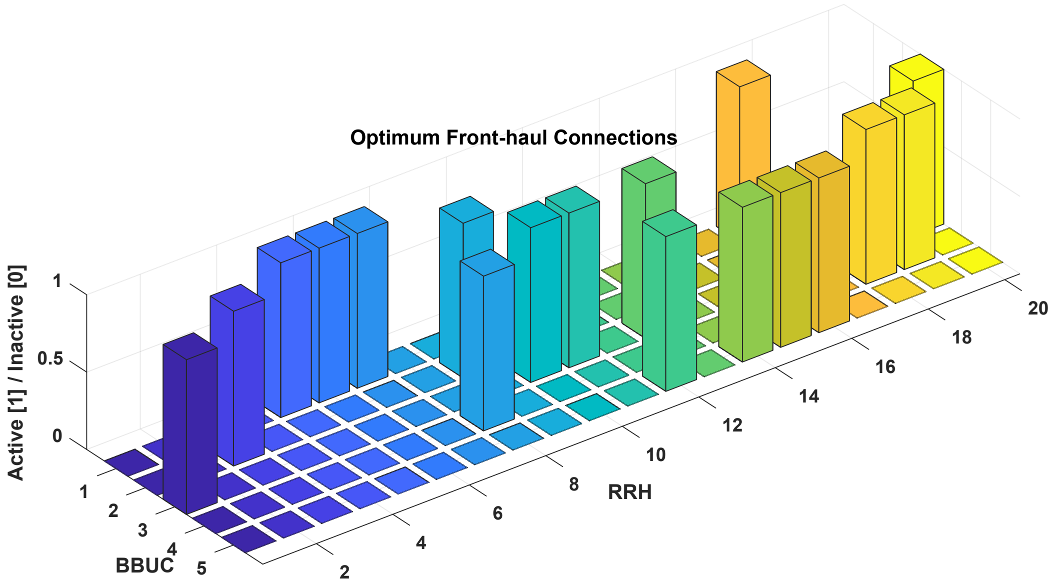

Figure 6.12: Optmized Front-haul connections of RRHs with BBUCs using equation 6.1

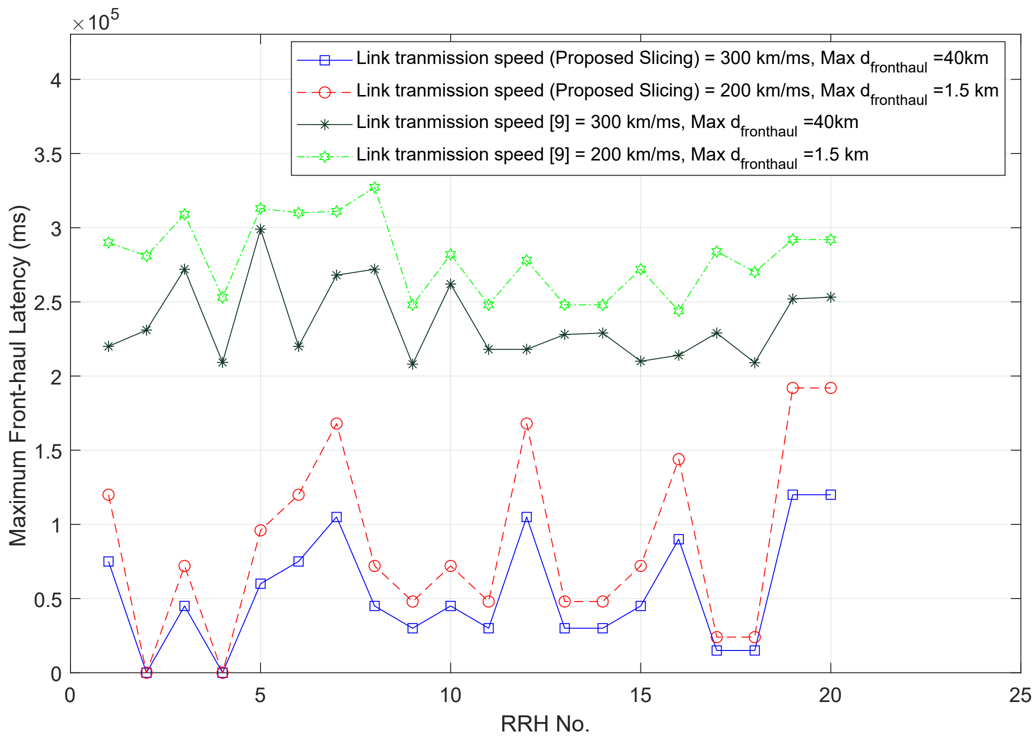

Figure 6.13: Comparison of E2E Latency of proposed scheme with 5G VANET architecture [9]

1.2ms for Fibre link and 1.9ms for microwave link. However maximum E2E latency of previously proposed 5G VANET architecture [9] is 3ms (for fibre link) and 3.3ms (for microwave link). The promising results of proposed slicing framework affirm that E2E latency of critical services in 5G can be supported with reliability as high as 99.99%. Therefore, the proposed slicing solution meets both KPIs (i.e., Ultra reliability and low latency) for mission critical services.

6.6 Conclusion

In this chapter, an E2E network slicing framework is presented to achieve desired level of QoS provisioning among customized services in 5G-driven VANETs, by considering both RAN and core network, which is a key challenge of 5G networks.

Through SDN-enabled NFV technology, the proposed framework distributes some services of 5G core close to cell sites using Mobile Edge Computing (MEC) technology and, keep other services with centralized processing, to meet desired levels of KPIs. Furthermore, a dynamic radio resource slice optimization scheme is formulated mathematically, to implement network slicing for mission-critical and and best effort traffic in 5G-driven VANETs. The solution is solved using GA by keeping in view the resource elasticity requirements.

It is concluded from simulation results that the proposed slicing scheme achieves the desired levels of end-to-end reliability and timely delivery of mission-critical traffic.

Chapter 7

Conclusion and Future Directions

In this chapter we conclude the summary of the contributions and results, and a number of interesting future directions are listed.

7.1 Conclusion

Next generation Vehicular Ad-hoc Networks (VANETs) will be dominated by exponential growth of heterogeneous data traffic, including additional massive diffusion of Internet of Things (IoT) traffic. The exponential growth of heterogeneous data traffic and diversified quality of service (QoS) demands poses significant challenges for current Vehicular Ad-hoc Networks (VANETs) and is one of the primary reasons for the evolution of next generation 5G-driven VANETs. To meet these challenges, network resources need more flexible and optimized resource allocation strategies.
According to our vision, this evolution can be achieved by transforming VANETs into a more flexible and programmable fabric with a globalized view. This objective can be acquired by jointly utilising 5G-driven technologies (such as Cloud-RAN, SDN and NFV) by providing a multitude of diverse services and resource sharing over a common underlying VANET infrastructure. Besides these technologies, Edge Computing and Fog Computing technologies are also playing important roles in offering ultra low latency, high resource utilization, and real-time access to radio access. These 5G-driven technologies are expected to substantially improve communication and resource sharing over a common underlying physical infrastructure of VANETs.

Researchers have explored multiple solutions for optimized communication in VANETs but no work has yet been proposed which advise different frameworks and optimization approaches addressing resource allocation with the 5G perspective.
In this thesis, we aim to propose efficient algorithms and approaches to provide optimized communication and resource allocation in 5G driven VANETs. In this chapter we provide the summary of the results and contributions.

7.1.1 Literature Review

A comprehensive literature review of heterogeneous Vehicular Ad-hoc Networks and 5G-driven technologies such as Software Defined Networking (SDN), Cloud-Radio Access Network (C-RAN), Network Function Virtualization (NFV) and Edge Computing along-with their implementation in VANETs is presented. The following conclusions are drawn from the literature review;

- Current heterogeneous VANETs using different wireless access technologies such as 4G, LTE, LTE with D2D and 3GPP cannot be easily well cooperated under the traditional VANET architectures. Consequently, a large number of of wireless network infrastructures and spectrum resources are wasted, thereby leading to the low quality of experience (QoE) of vehicle users. There is a need to rethink current VANET architecture, to turn it into a more flexible and programmable fabric enabling a globalized view of all resources.

- The management and control of vehicular networks on a large scale becomes a major challenge due to ever increasing vehicular network size and highly evolved physical layer technology [3].

- The frequent handoffs between different cellular infrastructures due to high mobility and rapidly changing topology of VANETs becomes another major challenge.

- To provide consistency in services with the frequent topology changes and varying QoS demands, the heterogeneous substrate must have a global view of all service requests, to provide network functionalities more efficiently on large scale.

- Integrating 5G enabling technologies such as Software Defined Networking (SDN), Network Function Virtualization (NFV), Cloud-RAN (C-RAN) and Fog/Edge Computing, VANETs are expected to provide solutions for these challenges.

7.1.2 5G Next generation VANETs using SDN and Fog Computing Framework

A detailed description of high level design of the proposed 5G-driven architecture which includes; description of physical topology and logical structure of architecture and, the roles of each component contributed in the architecture are discussed. A new Fog Computing (FC) framework is also discussed. Some benefits of the proposed architecture associating its feasibility in HetVANETs are also discussed. Simulation is performed to investigate the performance of architecture by comparing the transmission delay, throughput and control overhead on controller with other architectures. From the simulation and results, it can be seen that the throughput is improved, and transmission delay and control overhead on controllers is also minimized in comparison with previously proposed architectures.

7.1.3 An Evolutionary Game Theoretic Approach for Stable and Optimized Clustering in VANETs

An innovative Evolutionary Game Theoretic (EGT) approach is proposed to automate the clustering of nodes and nominations of cluster heads, to achieve cluster stability in VANETs. The equilibrium point is proven analytically and the existence of evolutionary equilibrium is also verified using the Lyapunov function. The proposed game is tested and analyzed with different number of clusters for different populations of vehicles and cost functions. An optimal cost is suggested that defines an optimum clustering.

It is concluded from the simulation and results that the proposed approach is lightweight and semi-distributed, and allows faster convergence. Furthermore, the signalling overhead and complexity of proposed approach is minimized and the switching rate of cluster heads is also reduced in comparison to ALM clustering [8].

It is also analyzed through simulation and results that the proposed framework is able to maintain cluster stability, as the clusters evolve towards balanced sizes and system is converged with an average total throughput of clusters.

7.1.4 A Hybrid-Fuzzy Logic Guided Genetic Algorithm (H-FLGA) Approach for Resource Optimization in 5G VANETs

A hybrid Fuzzy Logic guided Genetic Algorithm (H-FLGA) approach is proposed for the SDN controller, to support optimum resource allocation over our proposed 5G-driven VANET architecture in Chapter 3. The proposed approach facilitates the network service providers to implement a more customer-centric network infrastructure thus improving their spectral efficiency. A multi-objective resource optimization problem is formulated, where five different objectives of resource provisioning are combined and solved using a hybrid approach. The proposed Fuzzy Inference System (FIS) is used to optimise weights of multi-objectives depending on the Type of Service (ToS) requirements of customers.
It is concluded from the simulation and results that the value of multi-objective cost function of proposed hybrid H-FLGA approach is minimized as compared to GA. The proposed approach is flexible to set weights of multi-objectives, depending on QoS demands and requirements of different users.

7.1.5 An End-to-End (E2E) Network Slicing Framework for 5G Vehicular Ad-hoc Networks

An E2E network slicing framework is proposed with the consideration of both the radio access network resources and the core network resources in 5G-driven VANETs. Moreover, a dynamic radio resource slice optimization scheme is also formulated, that handles a mixture of both best-effort traffic and mission-critical traffic, by keeping in view resource elasticity requirements.
The problem is solved using Genetic Algorithm (GA) and the results are compared with our previously proposed 5G VANET architecture in chapter 3. It is analyzed from the simulation and results that the bandwidth slicing ratios are optimality ad-

justed and the network dynamically adapts to instantaneous network load conditions in a way that a targeted KPIs are guaranteed.

7.2 Future Directions

In this section, based on the assumptions, results and observations discussed in this thesis, a number of interesting future research directions are listed below;

- In Chapter 3, the performance of proposed 5G-driven VANET architecture is investigated through simulation, by comparing the transmission delay, throughput and control overhead on controller with other architectures. It would be very useful to investigate the performance of proposed architecture through a real test bed for SDN based system and comparing the result with the simulation result. The test-beds can give more realistic and accurate results towards the real-life scenarios.
  Future challenges include, optimizing route selection, designing protocols at SDN controller for load balancing, improving service efficiency provision, due to massive traffic increase for 5G-driven VANETs.

- The proposed Evolutionary Game Theoretic (EGT) approach in chapter 4 paves a way towards stable and optimized clustering in VANETs. The proposed EGT approach can further be extended by analyzing the efficiency of the proposed game on the overall protocol stack using a network simulator. Furthermore, investigating it over different VANET routing protocols such as AODV, DSR, DSDV, OLSR, using a real test bed or network simulator can quantify the efficiency of proposed approach.

- The proposed H-FLGA approach in chapter 5 can further be extended by considering multiple resource sharing scenarios by using OpenFlow and Mininet. The performance of proposed scheme can further be quantified through extensive simulations, by taking energy consumption into account. Future directions include the possibility of implementing the proposed method in future ultra-dense networks, especially its implementation in computation offloading and resource allocation in ultra-dense networks. Furthermore, the proposed approach may be tested using OpenFlow and Mininet.

- Our proposed E2E network slicing scheme in chapter 6 can further be employed to analyse customised 5G VANET scenarios with different KPIs, which involve transporting different flows on a complex network, including RAN and CN to compete for resources during transmission, buffering, and computing. However, network slicing for the 5G era is still shaping up, with most of the concerns and issues remaining unsolved.

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