DESIGNING OF VEHICULAR AD-HOC NETWORKS WITH IMPROVED PERFORMANCE APPLICABLE TO INTELLIGENT TRANSPORTATION SYSTEMS

THESIS SUBMITTED BY
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Statement of Originality

I, Sreya Ghosh, registered on 10th July 2019, do hereby declare that this thesis entitled **"Designing of Vehicular Ad-hoc Networks with Improved Performance Applicable to Intelligent Transportation System"** contains a literature survey and original research work conducted by me as part of my Doctoral studies.

All the information presented in this thesis has been obtained and documented in compliance with existing academic rules and ethical guidelines. I affirm that, as required by thesis regulations and ethical conduct, I have fully cited and referenced all materials and results that are not original to this work.

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Sincerely,

Sreya Ghosh.

Abstract

Intelligent transport systems (ITS) yield fruitful solutions to manage traffic problems. ITS includes all approaches of transportation likewise air, rail, road, and water. Interrelation and collaboration of various components of each mode ensure the successful implementation of ITS. The research work in the thesis is performed in accordance with the objective of implementing a well-developed ITS, with adequate capacities to handle the transport demand. Modern ITS are being propelled by the development and adoption of wireless telecommunications and computing technologies, thereby allowing that our roads and highways can be both safer and more efficient transportation platforms. This has motivated me towards performing an exhaustive survey of the existing works in the domain of ITS during the period. Generally, ITS uses stationary infrastructures called roadside units (RSU) to communicate with the traffic management centre for data collection, analysis, and control operations. RSUs contribute to data dissemination, traffic predictions, and management. However, RSU deployment requires huge installation and additional maintenance cost that trigger a significant research domain that deals with optimal placement of RSUs. Identifying the placement positions that provide maximum coverage and network performance so that we can cover the transportation region with the reduced number of RSUs are one of our primary areas of this research. A novel optimal RSU deployment framework (IIA-ORD) is proposed based on complex network analysis of considered transportation network. IIA-ORD follows the idea of deploying RSUs in the crucial road intersections that are significant in terms of commercial and educational uses. Different criteria and their evaluated values are used to identify the deployment positions like degree centrality, betweenness centrality, eigen vector centrality, derived cumulative traffic connection and modified K-shell index. Then multi-criteria decision-making formulation TOPSIS is used to build the final candidate list of positions used for RSU deployment. After a set of simulations and comparisons to recent existing RSU deployment schemes, the outcomes exhibit the significance of the proposed IIA-ORD in terms of average area coverage, average connectivity, contacts per trip, end-to-end delay, PDR, and number of RSUs. Finally, the effectiveness of the system is established by implementing a traffic prediction framework by placing RSUs in every intersection with our proposed scheme based on the accuracy and loss analysis. After the execution of traffic

prediction application in the RSUs, the next important objective is to control them in accordance with the estimated traffic. To this end, in this thesis, we develop an energy efficient RSU scheduling formulation where RSUs active or standby status are handled by the central controller based on the predicted traffic. To support high data rate requirement of VANET millimeter wave based RSUs are used for this formulation. It is evident that efficient VANET routing protocol plays crucial role in the accomplishment of applications like emergency message awareness, dynamic route planning using 802.11p standard dedicated for wireless access in vehicular environments (WAVE). Traditional mobile ad hoc network (MANET) routing and forwarding protocols have failed to provide standard performance for VANET and suffered from rapid link failures. In the thesis, it is shown that routing protocols that incorporates location specific functionalities and mobility constraints in their designs deliver better quality of service (QoS) performance. Bio-inspired algorithms are advanced emerging paradigm used in VANET routing due to their remarkable advantages. They are useful in addressing VANET optimization problems in searching accurate solutions to enhance vehicular networks performance. In the initial phase of VANET routing protocol designing, we propose an advanced version of ant colony optimization (ACO) based routing protocol named as reduced route overhead by ACO (RRO-ACO). It is influenced by the information distribution process of ants through their pheromones distribution process for discovering most stable route for data transmission. Vehicular nodes broadcast forward ant packets and link stability is accounted for identifying most stable route. Once the control packet is received at present hop, acknowledgement packets are used to minimize the further broadcasting of control packets by the previous hop. Performance evaluations of RRO-ACO with state-of-the-art routing protocols gives improved results in terms of PDR, overhead and latency. In the next phase, we propose a new bio-inspired VANET routing protocol called canine olfactory route-finding algorithm (CORFA). CORFA is inspired from the canines' unique message passing capability through barking where distance is inversely related to loudness of barking. Moreover, CORFA motivates by canines' distinctive behaviour of remembering past discovered environment. At the time of packet forwarding, vehicles request previously discovered routes from RSUs for avoiding route discovery process that ensures reduced network overhead. Here QoS parameters are compared for different scenarios like varying source to destination distance, packet size, vehicular speed and density to establish the effectiveness of proposed algorithm. Convergence analysis is also done in comparison with the existing bio-inspired VANET routing protocols. After the incorporation of optimal infrastructure placement and QoS aware routing, the further prime objectives of this dissertation are to alleviate traffic congestion and minimize environmental pollution, which directly improve passenger safety and comfort. To this end, we propose a RSU assisted variable speed limiting (VSL) system to alleviate the gathering of vehicles at the intersection. Static speed limiting systems are futile to manage traffic congestion, so our formulated VSL model is capable to ease congestion at intersections. For passenger benefit, existing navigation systems like Google provide shortest and fastest route for users. Nevertheless, the suggested route is not tailored to users' requirements. Considering this, we have developed a users' criteria-based path planning for finding appropriate healthcare destination that avoids unnecessary wastage of time. At the time of emergency, our developed application recommends exact destination for patients, which can be lifesaving. When compared to the baseline path-planning algorithm Dijkstra, our proposed system outperforms in terms of travel time and computational time. While VSL systems control vehicular speed to handle traffic congestion another worthwhile way to manage traffic congestion is to re-route the vehicles in multiple routes. As road resources and options for re-routing are fixed, so we cannot re-route to a particular road in a repetitive manner. Besides that, public vehicle follows pre-determined route so only private vehicles can change their route according to the traffic situation. Post pandemic era enforces physical distancing which increases the inclination of using private cars, which creates more congestion. To resolve aforementioned issues, we have proposed enhanced A* algorithm that differentiate private vehicles, re-routes them according to road condition and stops recurrent usage of a road. Reduction of travel time and waiting time generate less acceleration and deceleration, which save carbon emission and fuel consumption. Supremacy of this proposed algorithm is established by comparing it with conventional Dijkstra and A* algorithms. With the envisioned era of machine learning, ITS have evolved as more impactful tool for traffic and pollution management. Finally, by leveraging our already implemented optimal RSU deployment scheme we develop a traffic management system called RSU assisted federated learning-based traffic management (RATM-FL) that works in collaboration with a central cloud server. It is enriched with a federated learning framework to ensure enhanced system performance and safety. Distributive RSUs handle local traffic using BiD-LSTM model and federated learning is used to manage global traffic through a central cloud server. We validate our proposed model with extensive simulation study in comparison with the existing traffic management systems. Our results indicate that RATM-FL outperforms in terms of carbon emission, fuel consumption, travel time, waiting time and vehicular speed. So far, we have explored the requirement of optimal infrastructure deployment and smart functionalities for cost-efficient and energy-efficient VANET.

The evolution of autonomous driving and next-generation vehicular applications demands communication systems capable of handling high traffic loads with ultra-low latency and high reliability. Vehicle-to-everything (V2X) communication has emerged as a vital paradigm, with Cellular V2X (C-V2X) becoming increasingly prominent due to advancements in 5G and forthcoming 6G networks. C-V2X enables autonomous resource allocation in a distributed manner, it faces significant challenges such as resource conflicts, collisions, and Quality of Service (QoS) degradation in dense traffic scenarios. To encounter these discrepancies a novel Cluster Head assisted Q-learning-based Resource Allocation (CHQ-RA) framework is proposed. To coordinate resource distribution, Cluster Head Vehicles (CHVs) are selected based on stability metrics such as speed, acceleration, and probability of successful packet delivery. A Q-learning algorithm dynamically adjusts the sensing window for CHVs which optimizes network performance by adapting to real-time traffic conditions. Additionally, a fitness function is employed to prioritize vehicles for balanced and efficient resource allocation. Simulation results demonstrate that CHQ-RA significantly outperforms traditional Mode 4, and existing relevant methods in key metrics, including Packet Reception Ratio (PRR), Collision Ratio (CR), and Update Delay (UD). The proposed approach effectively enhances performance and reduces collisions in dense traffic environments offering a promising solution for improving resource allocation in vehicular networks.

Considering the challenges of vehicular networks including the rapid topology changes and highly mobile environment, bio-inspired VANET routing algorithms are developed to increase QoS performance. Finally, the thesis addresses transportation network shortcomings including congestion and pollution to achieve smooth, safer, and cleaner traffic.

Dedicated to my family and my teachers.

Table of Contents

List of Figures

Chapter 5

Chapter 6

List of Tables

List of Abbreviations

ITS	Intelligent transportation systems
RSU	Roadside units
OBU	On board units
DSRC	Dedicated short-range communications
WAVE	Wireless access for vehicular environment
VANET	Vehicular ad-hoc networks
MANET	Mobile ad-hoc networks
ACO	Ant colony optimization
PSO	Particle swarm optimization
QoS	Quality of service
QoE	Quality of experience
LTE	Long term evolution
4G	Fourth generation
5G	Fifth generation
VSL	Variable speed limit
IoT	Internet of things
GPS	Global position systems
LSTM	Long short-term memory
RNN	Recurrent neural network
MCDM	Multi-criteria decision making
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
PDR	Packet delivery ratio
SUMO	Simulation of Urban Mobility
OSM	Open Street Map
TraCI	Traffic Control Interface
SB-SPS	Sensing based semi-persistent scheduling
CAV	Connected automatic vehicles
C-V2X	Cellular vehicle to everything
V2V	Vehicle to vehicle
V2I	Vehicle to infrastructure

1.Introduction

Outline of the Chapter:

1.1 Overview of ITS

"There can be no doubt that the transportation sector is the most critical sector of our economy." — Robert Brady, Writer

The enhancement of the economy and mobility demand of humankind, dependent upon the growth of transportation worldwide, is the root cause of enormous traffic congestion, resource wastage, environmental pollution, social degradation, and casualties from road accidents. It is the primitive requirement of human life to develop applications that come up with services concerning several transportation approaches. To increase transportation throughput, it is necessary to manage traffic to make it safer, smarter, and more coordinated. Therefore, the Intelligent Transportation System (ITS) and its collaborative technologies are globally relevant and significant. Intelligent monitoring and control of traffic flows to inform travellers about traffic and road conditions can alleviate the adverse impact of congestion [1].
Intelligent Transport Systems (ITS) is a multidisciplinary research field that can benefit in several aspects for developed and developing countries. In this chapter, we provide a comprehensive overview of ITS literature, to give a precise idea of all possibilities and applicability. This includes the information forwarding between vehicles-to-vehicles (V2V) and vehicles-to-infrastructure (V2I) to generate safer, efficient, and convenient transportation

systems by deploying optimal infrastructure. ITS infrastructure consists of RSUs, traffic lights, fog servers, and backbone servers [2]. Optimal deployment and functioning of these building blocks and their collaborative communication with vehicles and passengers ensure the success of ITS.

ITS includes technology, communications, and information to provide informed and efficient mobility and transport. It uses smart motorways, autonomous/driverless and connected vehicles, urban and suburban traffic control, execution of variable speed limits, transport safety and security, and improved mobility. ITS optimizes existing infrastructure placement to make the transportation sector more efficient, rather than to provide additional physical infrastructure with its environmental hazards and financial expenditure. The evolution of informatics and communication methodologies ensures the successful accomplishment of numerous applications defined by impactful technological content, used for management and control in the transportation domain. Supervision of vehicular traffic by acquiring traffic data, traffic signal timing management, access control, parking allotment, and distribution of logistics are substantial instances of how the ITS are becoming an exquisite tool for mobility management. The ITS aims to enhance transportation efficiency by addressing congestion, improving accident avoidance, and increasing emergency awareness [3]. Intelligent algorithms are developed to implement specific assumptions based on information exchange between vehicles and infrastructure. The travellers, referring to the traffic information given by ITS systems, could vary their decisions, allowing the termination of congestion. This section discusses the fundamentals of ITS overview, including its key components, standards, communication technologies, data collection methodologies, application areas, and underlying challenges in sections 1.1.1, 1.1.2, 1.1.3, 1.1.4, 1.1.5 and 1.1.6, respectively.

1.1.1 Key Components

VANET is a class of Mobile ad-hoc networks (MANET) which is exclusively designed for vehicular communications. Smart vehicles communicate wirelessly among themselves and infrastructure with V2V and V2I communication. These vehicles are equipped with on-board units (OBU) and GPS services. RSUs are placed throughout the transportation network and to transmit data to vehicles other RSUs and backend servers. It acts as a transceiver system that also has processing capability to control the traffic. Smart traffic lights are used to provide a dynamic traffic light cycle that overcomes the limitations of static traffic light systems. Vehicular cloud is incorporated into the ITS building blocks to manage and process huge traffic data, and requests and provide high-speed cellular connection to them [4] [5]. Figure 1.1 illustrates a Vehicular Ad Hoc Network (VANET) system that effectively highlights the interactions within VANET, demonstrating how vehicles, infrastructure, and cloud systems work together to enable intelligent transportation systems.

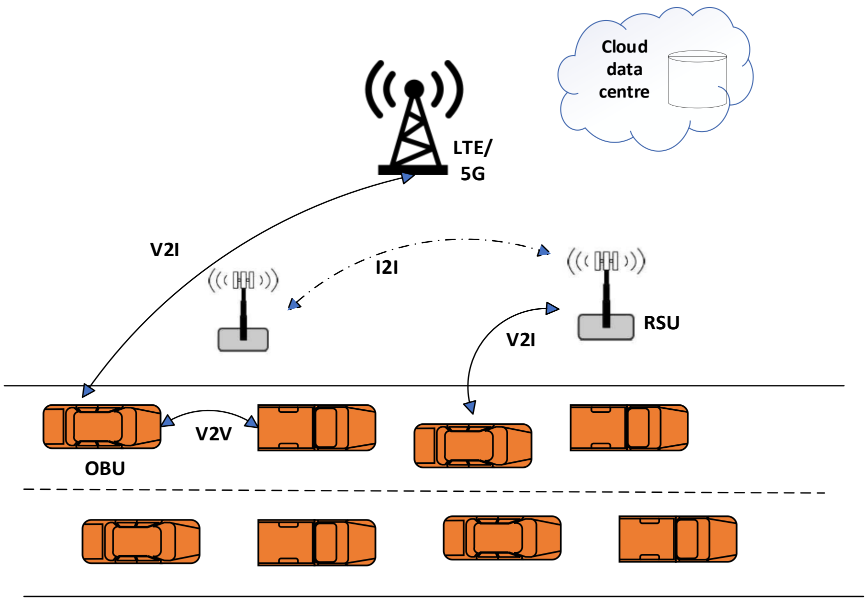


Figure 1.1 VANET architecture

1.1.2 ITS Standards

To address the challenges of ITS and its enormous applicability, the IEEE 802.11 task group was established in 2004 to bring advancements of the IEEE 802.11 standard for the formation of Wireless Access in Vehicular Environments (WAVE). As a result, the IEEE 802.11p standard was issued in 2010 (draft v11) that grants the application of the licensed ITS band of 5.9 GHz to initiate communications for highly dynamic vehicular networks. IEEE 802.11p PHY layer follows orthogonal frequency division multiplexing (OFDM) having a channel bandwidth of 10 MHz. It supports data rates ranging from 3 to 27 Mbps with a maximum communication radius of 1 km. The MAC layer of IEEE 802.11p implements an enhanced Distributed Coordination Function (DCF) algorithm, adapted from the existing IEEE 802.11 standards. Recent advancements in channel access algorithms incorporate Quality of Service (QoS) concepts to prioritize delay-sensitive messages, particularly those related to safety issues [6]. Recently, the IEEE working group 1609 defined additional superior layers that are above PHY and Mac layers. (i) IEEE 1609.1 includes resource management; (ii) IEEE 1609.2 manages security services; (iii) IEEE 1609.3 gives routing and addressing services; (iv) IEEE 1609.4

provides supporting multi-channel operations; (v) IEEE 1609.5 enables layers management; and (vi) IEEE 1609.6 manages the application functionalities. The collaboration of the IEEE 802.11p and IEEE 1609 standards is denoted as Wireless Access in Vehicular Environments (WAVE) [7].

1.1.3 Communication technologies in VANETs

Vehicular communications enable data transmission between all types of devices including vehicles, infrastructures, traffic lights, fog nodes, and cloud servers that signify the umbrella term V2X (vehicle-to-everything) communication. This communication establishment is difficult to maintain reliability and low latency because of the dynamic mobility environment of vehicular networks.

- *Vehicle-to-vehicle Communication:* In this form, vehicles can communicate with neighbour vehicles through single-hop or multi-hop links in an ad-hoc manner.
- *Vehicle-to-pedestrian Communication:* V2P communication connects vehicles and pedestrians through wireless technologies, improving road safety and mobility. Using DSRC or C-V2X, vehicles broadcast their presence, speed, and direction to nearby devices. Pedestrians with smartphones, smartwatches, or wearables equipped with V2P apps receive alerts or send signals to vehicles.
- *Vehicle-to-infrastructure Communication:* Vehicles communicate with infrastructure. When the infrastructure is a roadside unit then it is called V2R (Vehicle-to-roadside) communication. Another version of this is V2N (Vehicle-to-network) where vehicles exchange information with the network through 5G/LTE communication. Infrastructure like fog servers, smart traffic lights, and RSUs can communicate with each other for information sharing which is denoted by I2I (infrastructure-to-infrastructure communication). The final communication technology is V2C (Vehicle-to-cloud) Communication where vehicles and central cloud servers take part in information transmission [8].

VANET can function in a fully distributed, centralized or hybrid manner that collaborates V2V, V2R, and/or V2P communication technologies as depicted in Figure 1.2 [9].

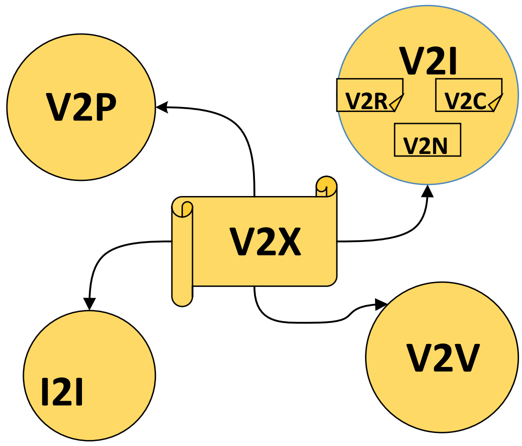


Figure 1.2 Vehicular Communication Technologies

1.1.4 Data Collection Methodologies

To come up with any ITS application the foremost thing we require is information from the roadways. Efficient traffic-data accumulation is required to predict and control the traffic condition and address congested road networks in dense developing urban areas that have chaotic road networks. Sensors on roads give such knowledge. We can categorize them as static, mobile and hybrid sensing. Static sensing means sensors are placed in a fixed manner on the road; mobile sensing means sensors being deployed in ongoing vehicles and finally in hybrid sensing both in-vehicle and roadside infrastructure perform together.

Static Sensing: Video monitoring and image capturing are effective tools for analysing traffic density, estimating speed, and detecting incidents. Magnetic sensors and loop detectors, embedded beneath the road surface, are used to gather data on various parameters, such as vehicle size and speed. Applications of loop detectors include distinguishing different vehicle types based on size, identifying traffic conditions using speed data, and managing intersections by measuring vehicle queue lengths [10].

Mobile Sensing: Moving on road vehicles can also fetch road information. Introduction of GPS and mobile phones make the process famous and feasible. GPS enabled vehicles and smart phones with gyroscope, accelerometers, magnetometers, microphone, camera etc., collect and transfer road information [11].

Hybrid Sensors: Now-a-days RFID tags are attached on vehicles and RFID readers on roads to identify vehicles and gather information like travel time, densities etc. Roadside installed Bluetooth detectors recognize Bluetooth radios from phones inside vehicles. Cell phone operators supply approximate traffic densities in the nearby cell tower based on subscribers seen at that tower. Tele density, Bluetooth or RFID tag can provide travel time information as they distinguish individual vehicles through unique ID that can be the cell number or Bluetooth MAC or RFID tag, and can re-distinguish the same vehicle at a different detector and calculate travel time between the detectors. GPS has better potential as it can operate without any detector installation on road [12].

1.1.5 ITS Applications

ITS applications can be categorized into three main sections: safety, comfortability, and finally efficiency. All of them are discussed in a precise manner.

Safety

As depicted in Figure 1.3, according to the Ministry of Road Transport and Highway Transport Research Wing of India, each year we lose 1.5 lakh lives on Indian roads due to road accidents means 47 accidents and 18 deaths every hour [13]. ITS plays a pivotal role in providing road safety and reducing accidents. Delay sensitivity is a very crucial point of this application area. Whenever any kind of mishap happens, the nearby vehicles should be alerted by an emergency message about the incident.

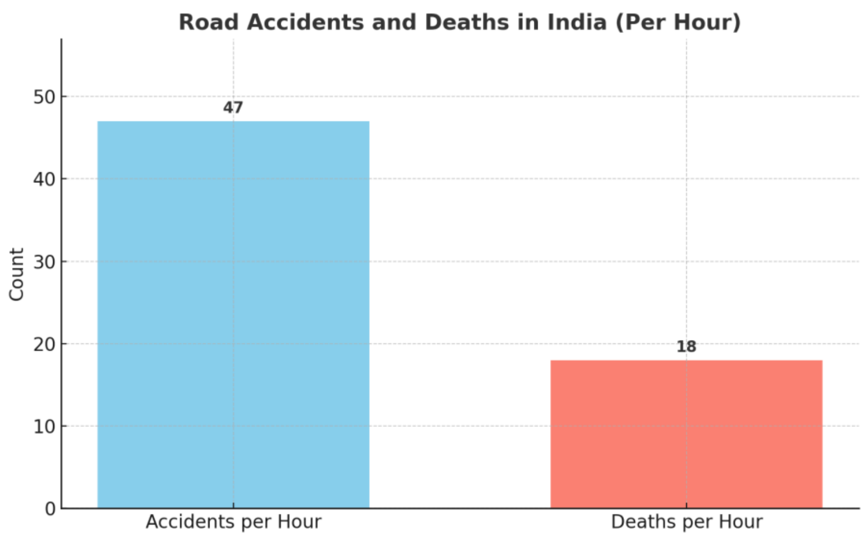


Figure 1.3 Road accidents and deaths in India (per hour)

Road condition monitoring and awareness about the vehicular environment such as weather conditions are the key factors of effective implementation of ITS. Therefore, information delivery, monitoring and managing the traffic are the ultimate goals of this application. Machine learning models not only estimate the future traffic status but also identify the roads that are prone to accidents so it can be avoided and save lives.

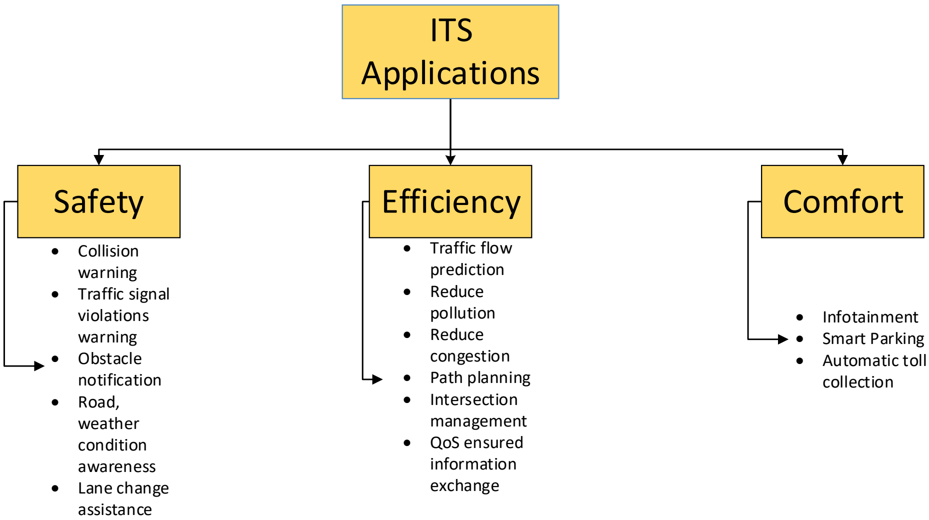


Figure 1.4 Summary of ITS applications

Comfortability

This application area prioritizes enhancing commuters' comfort and convenience while ensuring an efficient and stress-free travel experience. The key aspects are

i. Shortest Travel Time: Advanced routing algorithms and real-time traffic data analysis help commuters identify the fastest route to their destination. This minimizes delays caused by traffic jams, roadblocks, or accidents, thereby improving travel efficiency.

ii. Smart Parking Management: Locating parking spaces is often a time-consuming and frustrating task. Smart parking systems use sensors, connected devices, and mobile applications to guide drivers to available parking spots. These systems also allow pre-booking of spaces and facilitate cashless payments, saving time and reducing parking-related congestion.

iii. Navigation: Modern navigation systems go beyond basic turn-by-turn directions. They integrate real-time updates, alternate routes, and detailed maps to provide accurate and context-aware guidance. Features like voice-assisted directions and lane guidance further enhance safety and ease of use.

iv. Travel Time Estimation: Predictive analytics and historical traffic data allow accurate travel time estimations. These estimations help commuters plan their trips better and make informed decisions about when and how to travel.

v. Congestion Avoidance: Traffic congestion is a significant concern in urban areas. Intelligent transportation systems (ITS) use real-time data from roadside units (RSUs), vehicular networks (V2V and V2I communication), and traffic monitoring tools to identify congested areas and suggest alternative routes. Smart traffic lights dynamically adjust their cycles to optimize vehicle flow and reduce bottlenecks.

By integrating technologies such as the Internet of Things (IoT), cloud computing, and artificial intelligence, this application area aims to transform commuting into a seamless, efficient, and pleasant experience.

Efficiency

To implement efficient ITS, it is important to achieve reliable and high-speed device-to-device (D2D) communication. Proper traffic management is crucial to ensure less travel time, traffic jams and environmental pollution [14]. Figure 1.4 illustrates the summary of ITS applications. In this thesis, we have focused on the following ITS applications:

- In Chapter 4, an enhanced QoS-enabled VANET routing algorithm is proposed. Lower delay and reliable V2V and V2I communication are the basic requirements for emergency message transmission. Intelligent usage of roadside infrastructure reduces redundant route discovery for packet transmission.
- In Chapter 3, influential intersections are identified, and a cost-effective RSU deployment scheme is proposed. Historical traffic data is used to predict future traffic estimation.
- In Chapter 5, congestion control is achieved by implementing a dynamic speed-limiting system so that the accumulation of vehicles at intersection points can be avoided. Emergency healthcare destination finding and arriving in time is a life-saving application of ITS which is also proposed in this chapter.
- Chapter 6 delivers dynamic route planning systems. Firstly, static path planning algorithm A* is modified and then hybrid cloud-RSU-based ITS is proposed. Reduced travel time, waiting time, fuel consumption, CO_2 emission, and increased average speed enhance the efficiency of ITS.

We have shown all these applications to function in dense traffic scenarios through the implementation of systems on open-source transportation maps considering crowd-sourced traffic data of Indian roads. Applications in ITS are supported by various data collection methodologies, communication paradigms, and dedicated standards that are discussed in the previous subsection.

1.1.6 Challenges for implementation of ITS and areas needed to be focused

Smart transportation is an elementary part of a smart city. Intelligent handling of transportation issues guarantees the successful implementation of smart city design. Vehicular nodes communicate wirelessly via single-hop or multi-hop manner with each other and alongside infrastructure that has to deal with various challenges. To understand the possible research contributory areas, rudimentary challenges are discussed.

Rapid Mobility and Scalability: The vehicular environment is highly mobile; this makes the information exchange between vehicles very difficult. Execution of VANET routing protocols is a challenging task to deal with. Vehicles and fixed infrastructure collaboratively operate. As transportation areas and vehicles are growing day by day, it is desirable to deploy the infrastructure intelligently. Cost-effectively positioning the infrastructures is a mandatory requirement of VANET to sustain the limited bandwidth and high data rate. It should be the primitive goal to serve and connect as many vehicles as number of vehicles.

Radio channel characteristics: Radio channels for vehicular communication suffers from multipath propagation, weather impacts, and obstacles that degrade received signal strength. Vehicles move in relative speed with each other, which generates the Doppler Effect and further induces inter-carrier interference.

Reliable as well as low latency communication requirement: ITS applications aim to ensure safe and efficient transportation systems. In the event of an incident during transit, information must be promptly communicated to drivers or relevant authorities, enabling timely and appropriate actions. As a result, reliable and rapid data transmission is essential.

Rapid growth of vehicles: Effectively reducing and clearing traffic congestion is a crucial challenge in ITS design. Population enhancement, social distancing and consequently lesser use of public transport create traffic jam. As a result, roads have to handle traffic beyond their capacity. Prior and appropriate estimation of congestion and guiding the vehicles according to the situation plays a pivotal role for a successful ITS model.

Environmental Degradation: Pollution is a by-product of transportation evolution. Transportation damages the environment as an energy user. Vehicle emission is a root cause of air pollution. The use of ITS provides reduced travel time, efficient driving behaviour, road condition notification that optimize the fuel consumption and greenhouse gas emissions [15].

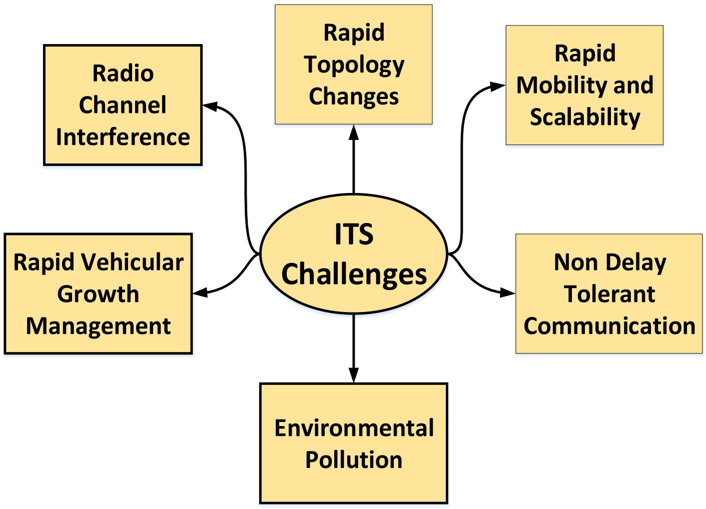


Figure 1.5 Summary of challenges faced by ITS

Thus, in this subsection, various distinctive challenges and constraints posed by ITS are deduced. Figure 1.5 summarizes the encountered challenges faced by ITS. Researchers and service providers work relentlessly to improve the system performance of ITS.

This section delivers a brief overview of the ITS background study and thereby establishes the motivation for the proposed work in this thesis.

1.2 Motivation

The primary motivation for organizing the proposed research work in this thesis is operated by two important factors that include:

1. The need to address the challenges within the transportation network and enhance ITS performance by reducing travel time and vehicle emissions through the implementation of the proposed methodologies.
2. The necessity of addressing design challenges in VANET through vehicular communication to achieve efficient routing, enhance transmission rates, manage large data volumes, support mobility, and optimize QoS parameters for ITS.

Accordingly, this section brings to light the pivotal areas of focus in the thesis by considering the shortcomings of the relevant works in the literature. Initially, any analytical experiment must be suitably demonstrated using real-life observations in either simulation models or test-bed prototypes. From the perspective of rapid vehicular mobility designing, open-source microscopic traffic simulator SUMO is employed because of its collaboration capability with several external simulators like OPNET, NS 3, OMNET, MATLAB, etc. This creates an enormous, diversified research platform [16]. Building on our expertise with the simulation model, we aim to optimize the ITS by improving traffic flow, reducing delays, and enhancing safety through data-driven insights and real-time system adjustments.

Due to instability of highly mobile inter-vehicular communication link denoted as Vehicle-to-Vehicle (V2V) communication technology, and the presence of traffic environment obstacles, roadside infrastructure was introduced to confirm the stability of the vehicular communication. The RSUs are mainly assigned for gathering, processing and forwarding traffic information obtained from smart vehicles. Besides that, RSUs are capable of influencing traffic flow of vehicles to ensure secure driving by taking decisions based on locally analyzed traffic data and transmitting emergency messages. The association between cars and Roadside Units (RSUs) introduced a new communication paradigm, Vehicle-to-Infrastructure (V2I) communication technology, aimed at enhancing Vehicle-to-Vehicle (V2V) communication performance. With the development of V2I communication, the link connectivity will be less prone to failure even though the network topology is extremely dynamic, especially when the sources are far away from the destination. The packet transmission between the vehicle and RSU are defined in two manners; when vehicles are in the direct transmission range of the RSUs that is single-hop or through multi-hop when vehicles are not in the RSU transmission area. Therefore, efficient RSU deployment framework is required in VANET so that the maximum number of vehicles can be served by the RSUs [17]. Besides that, due to the huge installation and frequent maintenance cost it is desirable to connect larger areas with limited RSUs. Because of its consequential effect in ITS enhancement, optimal RSU deployment emerges as a very captivating topic for researchers. Building on the state-of-the-art discussion summarized in Chapter 2, we focus on proposing an optimal RSU deployment scheme, detailed in Chapter 3. Most of the existing works target to improve network coverage with lesser number of RSUs but they did not consider the underlying transportation network topology and their static and dynamic centrality measures. It is mandatory to analyze the variation of traffic density of the junction points for understanding the dynamic nature of transportation network vertices. Moreover, crowd sourced traffic data would provide crucial insight into the varying traffic patterns of a region. Such knowledge can be exploited for efficient realistic feature incorporation of the nodes for the importance analysis. ***Motivated by the insufficient implementation of RSU deployment, our goal is to develop a system that tracks multiple attributes of intersections and integrates this data to assess the significance of infrastructure placement. Additionally, to demonstrate the effectiveness of our system, we focus on predicting traffic data for a larger region using a limited number of RSUs.***

VANET provides continuous exchange of information among vehicles and infrastructure through short range wireless communication that is supported by ITS for accomplishing plethora of applications. Before practical deployment of ITS, supporting technologies should be well executed. Vehicular wireless communication performance generally deteriorates and delivers poor quality of service because of rapid node mobility, interference, channel noise, and packet collision that may lead to delays in emergency information dissemination. Thus, to enhance successful packet transmission in vehicular networks, an efficient routing protocol must be designed and implemented by intelligent use of RSUs and vehicles [18]. From the point of view of vehicular application requirements, we aim to optimize the proposed routing protocol by four criteria that are packet delivery ratio (PDR), delay, overhead and throughput.

1. Packet Delivery Ratio (PDR) regards the ratio of successfully delivered data packets to the total packets sent to the destination.
2. Delay criterion refers to how quickly the information is delivered to the destination.
3. Network Overhead ensures minimal packet transmission to reduce unnecessary network load. Since each vehicle has its own information to forward, optimal broadcasting is necessary to minimize network expenditure.
4. Throughput measures the number of successfully received packets that arrive at the destination.

VANET has constraints that must be managed to optimize the aforementioned criteria. These constraints can be formulated as challenging optimization problems that are difficult to address using traditional optimization techniques. Bio-inspired algorithms are widely utilized for handling complex optimization problems. These methods gradually target to obtain near-optimal solutions in a timely fashion. Some of the reasons for their tremendous popularity among researchers are i) their reduced computational complexity, ii) they are generic methodology that means they do not require total problem knowledge, and iii) they can be adapted in terms of numerical accuracy, memory size, etc. [19]. All these properties motivated us to apply bio-inspired algorithms to address optimization problems in the domain of vehicular networks. ***Accordingly, our goal is to incorporate bio-inspired algorithms into VANET routing to enhance existing algorithms and demonstrate their effectiveness through experimental evaluation. Additionally, we aim to develop and propose novel routing algorithms that address the complex constraints posed by VANET.***

Having developed and optimized the basic ITS setup, the focus shifts towards addressing congestion and pollution management. A dynamic speed-limiting system is a possible solution of congestion mitigation [20] [21]. ***This motivates the next work in this thesis, which***

implements an RSU-assisted variable speed-limiting system to reduce traffic congestion. The next aim is to design a customized path for reaching a destination in an emergency by considering users' perspectives. The literature survey revealed that there has been limited contribution in this regard from the point of view of commuters.

Emissions from vehicles are the major cause of environmental pollution. Post-pandemic social distancing increases the tendency to avail private cars creating severe traffic jams. Rush driving, traffic congestion, and poor road conditions escalate pollution and travel time which deteriorate the quality of the transportation sector [22]. In this regard, the further motivation of this research is minimizing pollution and travel time. ***Accordingly, with the focus on reducing congestion, the next step of this work is to develop a novel re-routing framework that considers not only real-time traffic and road conditions but also the frequency of usage of a particular road so that continuous re-routing does not make it more congested.*** In our RSU deployment framework, we placed the RSUs only in the influential intersections, so the complete traffic information regarding traffic management of the larger area is yet to be explored. ***This encourages us for the next work in the thesis with the target to cut down congestion, fuel consumption, and CO_2 emission, which builds a complete design and implementation of RSU and cloud server-based ITS for traffic management of a larger region. The inclusion of collaborative machine learning-based methodologies between RSU and cloud servers enhances the system throughput and prediction accuracy.***

The emergence of connected and autonomous vehicles (CAVs) has created enormous possibilities for intelligent transportation systems (ITS). Cellular Vehicular-to-Everything (C-V2X) technology, particularly Mode 4, is crucial in ensuring direct communication between vehicles without involving infrastructure assistance [23]. This is essential for enabling road safety, traffic efficiency, and contextual awareness. However, the fruitfulness of C-V2X Mode 4 is hampered by key challenges, including inefficient resource allocation, packet collisions, and half-duplex constraints, which affect overall system performance. In C-V2X Mode 4, vehicles autonomously select resources for transmitting Cooperative Awareness Messages (CAMs) using a semi-persistent scheduling (SPS) approach [24]. While this mechanism ensures decentralized communication, it suffers from issues such as overlapping resource allocation and inadequate handling of dynamic traffic density, resulting in degraded packet reception ratios (PRR), increased update delays (UD), and high collision ratios (CR). These issues become more pronounced in high-density traffic scenarios, where resource contention intensifies and negatively impacts the quality of service (QoS). The final chapter is motivated by the need to increase the efficacy and reliability of C-V2X communication under diverse and dynamic traffic conditions. By addressing the limitations of existing SPS mechanisms and incorporating machine learning techniques, this work tends to enhance pivotal performance parameters such as PRR, UD, and CR.

To address these challenges, the endmost chapter of this thesis introduces a Cluster Head Vehicle (CHV)-assisted resource allocation framework, named CHQ-RA. By leveraging the stability of CHVs and integrating a Q-learning-based paradigm, this work aims to optimize resource allocation dynamically based on traffic density and link stability. The CHV serves as an intelligent agent, enabling adaptive sensing window allocation and efficient dissemination of resources among cluster members. The approach ensures better exploitation of available resources while meeting latency and reliability requirements.

It is thus deduced from this section that there is an immense motivation for conducting the proposed research work in the domain of ITS with QoS-ensured VANET routing features followed by its integration with traffic prediction and management for cost-efficient, pollution-controlled, and congestion-reduced transportation networks. In Figure 1.5 an overview of ITS literature and the explored research scopes are depicted. On this matter, the primary objectives of this thesis are figured out as follows.

1.3 Objectives of the thesis

I. **Developing smart functionalities and optimal deployment of Roadside Unit (RSU):** Our work focuses on designing algorithms to integrate smart functionalities into RSUs for the development of Intelligent Transport Systems, including

   1. Identification of Crucial intersections for effective RSU deployment so that number of RSUs are less for achieving reduced maintenance and installation expenditure.
   2. Congestion management between vehicles.
   3. Monitoring the transportation environment and detecting the suitable set of speed limits for vehicles.
   4. Analysis of historical and real-time traffic data and developing prediction models to optimize traffic parameters like travel time, fuel efficiency, waiting time, CO_2 emission, and fuel consumption.
   5. Efficient Path planning and route allocation of traffic with incorporation of vehicle classification.

II. **Vehicular Ad-hoc Network (VANET) Routing:** To upgrade road safety, robust VANET routing protocol formulation has become a mandatory requirement for ITS. The process of establishing and maintaining continuous connectivity among vehicles and infrastructures with QoS support is our ultimate target.

   1. Bio-inspired optimization techniques are explored to transmit packets among vehicular nodes as they have the potential to address the challenges associated with VANET routing such as vehicular network scalability, self-organized control of VANET's dynamics, complexity of messages exchanges, and VANET robustness.
   2. Superiority establishment of nature-inspired mechanisms over geographical and topological routing protocols.

III. **Efficient and adaptive resource allocation framework for C-V2X:** A potential solution is required to provide a scalable and adaptive framework for resource management in connected vehicular networks.

   1. Induce a resource management approach to mitigate the challenges of packet collisions and overlapping resource allocation in semi-persistent scheduling (SPS).
   2. Incorporate advantage of Q-learning to enable dynamic sensing window adjustments and optimal resource dissemination among cluster member vehicles to assist varying network conditions.
   3. Optimize pivotal performance indexes, including PRR, UD, and CR, establishing reliable and low-latency communication. Extensive performance evaluations through simulations will be executed to compare the proposed CHQ-RA framework with existing state-of-the-art works. Appraise its potency across scenarios implying varying traffic densities, CAM sizes, and transmitter-receiver distances.

By attaining these objectives, the thesis aims to contribute significantly to the enhancement of safer and smarter transportation networks.

1.4 Thesis Organization

The thesis is subsequently organized as follows.

- ❖ After the comprehensive discussions referring to the general introduction, motivation and outline of the thesis in Chapter 1, ***Chapter 2 provides the details related to the background literature of VANET architecture, optimal RSU deployment strategies, QoS-ensured packet forwarding, and efficient route guidance technologies.*** A technical overview of the underlying communication paradigm is provided as laid out by the IEEE 802.11p standard, an advanced amendment of 802.11a. Thereafter, we discuss a brief outline of the infrastructure and building blocks of VANET. A detailed sketch of the deployment of RSUs and their consecutive challenges follows this. In the next discussion, we focus on how the implementation of VANET routing protocols can be leveraged to encounter numerous challenges in terms of link failure, packet loss, etc. in transportation networks. Finally, we highlight how ITS platforms can alleviate the challenges faced by the traffic sector in terms of environmental pollution and congestion while also addressing the design challenges met during such implementations.
- ❖ The literature survey in Chapter 2 highlights a vast scope for implementing vehicular communication-based optimal RSU deployment in facilitating affordable ITS. Accordingly, the first step towards conducting state-of-art research is incorporating a real-life simulation model that will serve as a platform for validating analytical observations and facilitating performance validation and evaluation of designed ITS. Therefore, in Chapter 3, the transportation map is portrayed as a connected graph where intersections and connected roadways are vertices and edges respectively. The literature survey in Chapter 2 revealed several concerned areas in the existing roadside infrastructure deployment frameworks. Furthermore, limited work on both dynamic and static centrality analysis-based models to figure out influential intersections for RSU placement that ensure higher coverage time ratio, PDR, and contacts per trip duration. ***In Chapter 3, we implement a detailed influential intersection identification model in SUMO for traffic simulation, followed by network simulation, to cover a large geographic area using a reduced number of RSUs.*** In addition to designing an RSU placement strategy, another aspect that is of great significance is using the proposed model for traffic prediction application using the machine-learning model for sequential traffic data. A traffic-forecasting model will also provide important insight into the importance of roadside resources, which can be exploited further for information dissemination applicability. After examining relevant case studies from the

crowded metropolitan city of Kolkata, we utilize our developed simulation model for performance analysis.

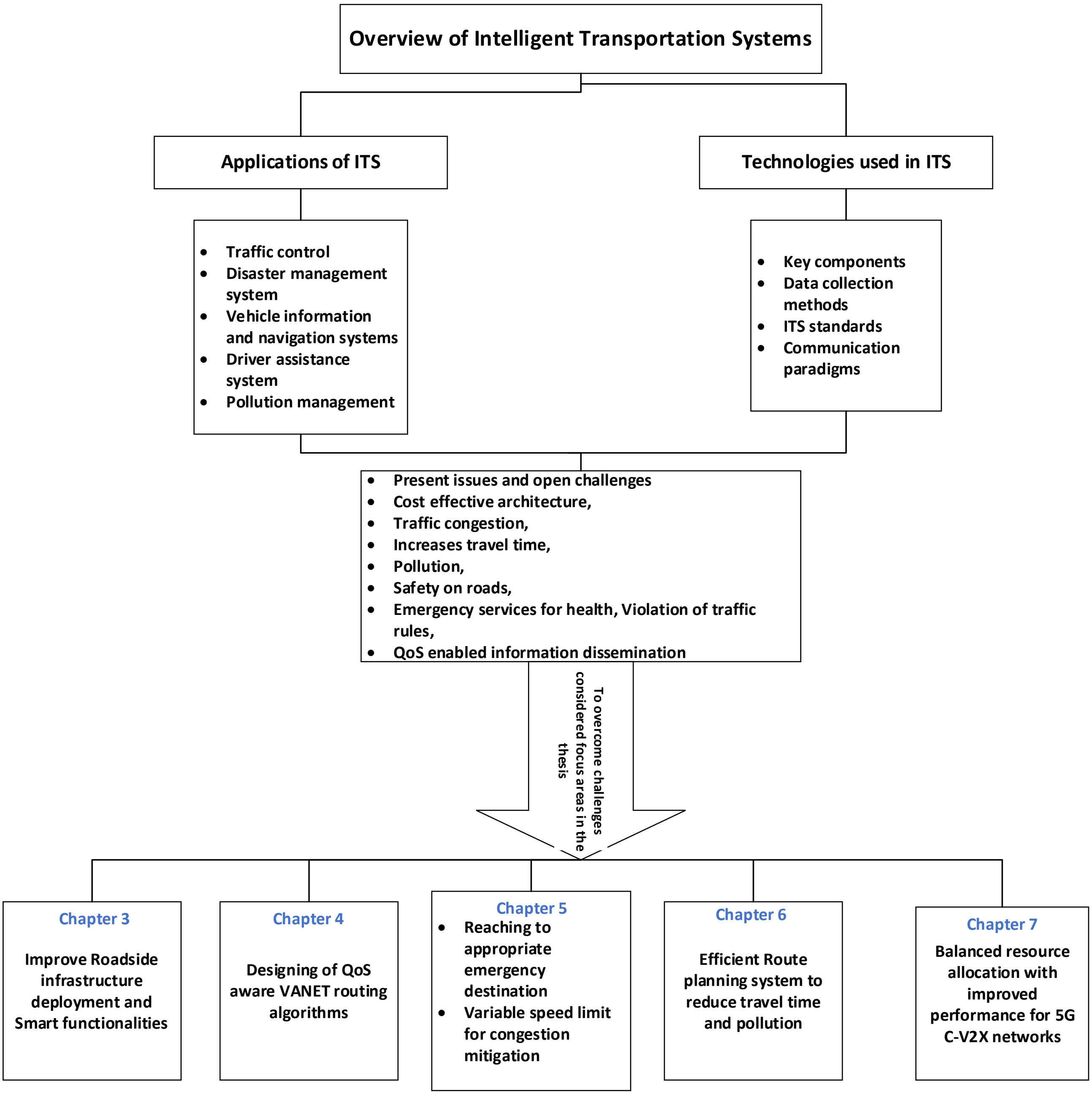


Figure 1.6 ITS overview and motivations

Finally, the accuracy of the traffic prediction model is validated by comparing it with the conventional RNN (Recurrent Neural Network) and the basic RSU placement scheme, where RSUs are deployed at every intersection. Moreover, the necessity of a higher data transfer rate along with lower latency stimulates the inclusion of 5G technologies in next-generation vehicular networks. Therefore, this chapter completes an energy-efficient operating approach of the 5G-enabled RSUs.

Publications:

1. **Journal:** Peer-to-Peer Networking and Applications, March 2023
2. **International Conference:** IEEE Codec 2023

❖ After optimizing, implementing, and identifying the critical intersections for RSU deployment in Chapter 3, as well as developing a traffic prediction framework, the next key objective is to address the challenges of rapid vehicular communication to facilitate VANET routing algorithms for low latency along with successful packet transmission. ***In this aspect, Chapter 4 deals with designing and implementing VANET routing algorithms that use roadside infrastructure strategically.*** Successful and fast packet transmission confirms the occurrence of numerous VANET applications like emergency message broadcasting, collision avoidance, road status awareness, etc. It is obligatory to reduce wireless packet transmission so that routing overhead will decrease. For this, we develop a VANET routing algorithm entitled as Reduced Routing Overhead using Ant Colony Optimization (RRO-ACO). The operation of packet forwarding is based on Ant Colony Optimization algorithm where acknowledgement is sent back to the previous hop to avoid redundant retransmission. This swarm intelligence-based formulation produces better QoS performance in comparison with existing noteworthy VANET routing algorithms. Furthermore, with the additional requirement of maximizing the QoS performance following multiple scenario changes like origin-destination distance, variable packet size, vehicular speed, and density we formulate our proposed work CORFA (Canine olfactory route-finding algorithm). As nature-inspired algorithms are self-organizing and require less computational complexity it proves to be the favourable choice for vehicular networks. Canines' capability to remember past environment and efficient message passing through barking makes them a great choice to adapt their mechanism in vehicular network for data transmission. Roadside unit storage is utilized to memorize successfully discovered routes so that it can reduce route discovery. Thereafter, we conduct a comprehensive performance evaluation for PDR, delay, overhead and throughput of CORFA with respect to different parameters that establishes its superiority in facilitating reliable and low latency data transmission by showing drastic improvement over the existing topological and geographical routing protocols.

Publication:

1. **Journal:** Transactions on Emerging Telecommunications Technologies, June 2023
2. **International Conference:** IEEE Applied Signal Processing Conference (ASPCON), 2020 Oct 7

❖ The focus shifts from the implementation of roadside network creation and vehicular routing to ITS application for traffic congestion control followed by optimal and customized path planning. ***Specifically, Chapter 5 deals with the monitoring and tuning of key performance indicators of ITS applications leading to comprehensive performance analysis and subsequent optimization by exploiting vehicular communication capabilities of vehicles and infrastructures.*** In this regard, a variable speed limiting system is designed to provide a suitable speed limit for drivers according to present road conditions. The proposed model reduces the gathering of vehicles at junction points so that congestion turns down with decreased travel time. Following this, to lend credibility to the proposed model we validate it through varying numbers of vehicles in simulation where vehicular speed is decreasing much faster in case of no speed limit control. Leveraging the ITS applicability is beneficial for finding suitable healthcare destinations in an emergency. Conventional path-finding algorithms only find the shortest path without considering the commuters' preferences. Finally, by taking note of the limitations of the static path-finding algorithms, we propose a multi-criteria decision-making approach that assesses users' criteria suggests apt hospital, and plans shortest route to reach there without any delay.

Publication:

International Conferences:

1. IEEE Calcutta Conference (CALCON), 2020 Feb 28
2. IEEE Calcutta Conference (CALCON), 2022 Dec 10

❖ Chapter 5 has already established the potential of ITS in relieving some of the major concerns such as congestion issues arising due to the abundant amount of traffic and the necessity for minimizing the travel time. However, in chapter 5 we have already shown the integration of dynamic path planning in place of static path planning systems reduces travel time. ***Consequently, in Chapter 6, we propose an enhanced version of the A* algorithm for route generation from source to destination.*** Post post-pandemic era boosts the inclination towards social distancing. Travelers opt for private vehicles rather than public transport that evokes traffic congestion scenario. As public transport follows a pre-set route by the authority, they cannot be rerouted according to the situation. To this end, in the proposed enhanced A* algorithm, private vehicles are rerouted based on real-time traffic conditions. Thereafter, through performance analysis we establish that it produces lesser travel time, CO2 emission, fuel consumption, waiting time in comparison with Dijkstra and A* algorithm. ***Having developed the simulation environment of ITS and VANET for small-scale area in chapter 3 and chapter 4 respectively, we now turn our focus towards a larger area of study and optimization followed by related design and implementation in chapter 6.*** To address this, we introduce our hybrid architecture based on the collaboration of RSU and cloud server that maximizes the coverage region. RSU serves smaller regions and generates local traffic forecasting model. Cloud server handles the areas that are not served by RSUs and generates global traffic prediction based on local traffic data from RSUs. For this purpose, we integrate federated learning framework between RSU and cloud server that minimizes computational overhead and delay. Detailed performance analysis is conducted to elaborate the remarkable improvement in travel time, waiting time, fuel consumption and CO_2 reduction over vehicular speed increment compared to recent established route guidance frameworks. Finally, the prediction model utility is established with respect to accuracy and loss performance comparison with respect to the centralized system.

Publication:

1. **Journal:** Submitted to Wireless Networks Springer Journal
2. **International Conference:** International Conference on Communication, Circuits, and Systems (IC3S), 2023 May 26

❖ Chapter 7 provides an overview of Cellular Vehicular-to-Everything (C-V2X) communication, emphasizing its functionality in connected and autonomous vehicles (CAVs). It enlightens the challenges associated with semi-persistent scheduling (SPS) in C-V2X Mode 4, including inefficient resource allocation, packet collisions, and the half-duplex problem. Cluster Head Vehicle-assisted Q-learning-based Resource Allocation (CHQ-RA) framework is proposed in this chapter. It explains the process of selecting Cluster Head Vehicles (CHVs) based on the stability index. The Q-learning-based dynamic sensing window allotment mechanism and the approach for resource dissemination among cluster member vehicles are described. This chapter validates system performance under varied scenarios used for performance evaluation. Results are analyzed to establish the superiority of CHQ-RA over existing methods in terms of

PRR, UD, and CR under varying traffic densities, CAM sizes, and transmitter-receiver distances. Comparative studies are included to validate the strength of the proposed framework.

Publication:

1. **Journal:** Submitted to International Journal of Communication Systems Wiley

1.5 Progress of the thesis with a summary of contributions

The following schematic figure 1.6 depicts the flow of the research contributions in this thesis.

Chapter	Content	Theme
Chapter 1	Overview of ITS, Building blocks, Applications, Data Collections, Standards, Challenges and Research findings, Motivation, Objective, Thesis Organization	Framing the research
Chapter 2	State of the art RSU deployment strategies and their limitations, Significance of VANET routing and relevant routing protocols, ITS perspective towards social and economical and environmental development	Literature review
Chapter 3	**Optimal RSU deployment based on complex network analysis** • A novel RSU placement scheme called IIA-ORD is proposed that outperforms in terms of average coverage ratio, PDR, E2E delay, and number of RSUs to cover the area • Scheme is validated by implementing a traffic forecasting application where Sbi-LSTM is used. **An Energy Efficient RSU Operating Scheme for 5G Enabled Intelligent Vehicular Networks** • A novel mm wave based RSU switching scheme is proposed that dynamically changes RSU state from standby to active according to predicted traffic condition. • Energy efficiency and number of active RSUs are observed over varying number of vehicles.	Infrastructure placement & functionality and Energy efficient infrastructure operation
Chapter 4	**Enhanced QoS Performance with Reduced Route Overhead by ACO Algorithm for VANET** • ACO based routing algorithm is proposed where control packet is broadcasted optimally so that number of packet transmission can be reduced. • PDR, delay and throughput is compared with existing schemes. **Improved Quality of Service by CORFA for VANET** • CORFA is proposed & implemented in VANET environment; previously discovered route is cached in RSU so that route discovery can be avoided. • Geographical and topological routing protocols are considered for comparison of PDR, delay, throughput and overhead according to varying vehicular density, speed, packet size and source to destination distance. • Convergence analysis is performed according to other bio-inspired routing algorithms.	QoS aware VANET routing is established through Stable packet forwarding
Chapter 5	**Controlled Speed Limiting System for Congestion Mitigation for Smart City Design** • Smart RSU controlled variable speed limit system for congested urban vehicular network is proposed. • Travel time is decreased and vehicular speed is increased in comparison with without speed limit control. **Developing an Application for Intelligent Transportation System for Emergency Health Care** • An web application is designed that considers user defined criteria to select appropriate healthcare destination and use bio-inspired algorithm to plan the path. Travel time and computational time are compared with conventional Dijkstra algorithm in simulation environment.	Variable speed limit system and Emergency route planning
Chapter 6	**Enhanced A* Algorithm to reduce CO_2 emission and fuel consumption in Intelligent Transportation Systems** • Advancement of A* Algorithm is proposed that uses not only the shortest distance but also real-time road condition and traffic information for re-routing. • As public vehicle follows pre-determined fixed route so only private vehicle is re-routed. • Algorithm supremacy is established in comparison with Dijkstra and A* in terms of waiting time, travel time, speed, CO_2 emission and fuel consumption. **An Intelligent Traffic Management for Smart Cities using Federated Learning based Congestion Predictions** • Optimally placed RSUs are used to predict and handle local traffic whereas central cloud server is used to manage global traffic and areas not covered by RSUs. Local and global traffic prediction is handled by federated learning based formulation. • System performance is evaluated based on Kolkata city based simulation where waiting time, travel time, speed, CO_2 emission and fuel consumption are taken as performance metrics.	Congestion and pollution control
Chapter 7	**Resource allocation framework for C-V2X CHQ-RA** • Leverages cluster head-aided resource management to enhance stability and reliability in connected vehicular environments. • Uses an adaptive Q-learning-based mechanism for sensing time allocation and real-time idle resource detection, taking traffic density into account. • Incorporates a fitness function that prioritizes vehicles based on their reliability and latency needs, scenarios to improve quality of service.	Balanced resource allocation for C-V2X networks
Chapter 8	Conclusion of results, Summary of contributions and discoveries and finally direction for the future research is provided	Concluding remarks

2

Background Study

2. Background Study

Outline of the chapter:

2.1 Introduction

"Learn from yesterday, live for today, hope for tomorrow. The important thing is not to stop questioning." — Albert Einstein

Comprehensive overview study in the preceding chapter has already put down the foundation for the proposed research work in the thesis. It is clear from the focus in this domain that ITS is envisioned as a crucial solution for providing a safer, more affordable, and faster transportation sector for citizens. The primary requirements of ITS is to ensure low latency and highly reliable transmission of traffic information from vehicle to infrastructure and vice versa while satisfying the strict QoS needs. Infrastructure deployment primarily concerns cost-efficiency and connectivity. Vehicular communication is prone to link failure due to its rapid scenario changes. It is challenging to maintain desirable QoS and implement efficient routing protocols. We review delay-sensitive routing protocols for packet forwarding which can provide rapid communication. Addressing the network latency issues in routing is emphasized to provide prompt awareness about collisions, accidents, and traffic-related information. With remarkable advancements in information and communication technologies, VANETs have gathered significant global attention. The integration of machine learning and deep learning frameworks enhances their capabilities by enabling intelligent decision-making, predictive analytics, and adaptive communication strategies. Once these primitive aims of establishing vehicular network with QoS enabled routing is achieved subsequently path planning from source to destination is induced in this research. All over, we elaborate the contributions of this thesis in relation to the discussed literature, to deliver significance to the research detailed in further chapters.

Therefore, in accordance with the objective of implementing an ITS, with adequate capacities to handle the transport demand, an exhaustive survey of the existing works has been done. The literature survey has revealed that although considerable theoretical and analytical works have been performed, still there are diversified research scopes that need to be addressed. Taking a cue from this, in the next section we outlined the contributions of this chapter.

2.1.1 Contributions of this Chapter

As ITS infrastructure deployment and subsequent VANET technologies have established their strong relevance in the transportation domains, this chapter provides a background study of infrastructure deployment strategies and QoS efficient routing algorithms followed by their applicability in performance enhancement of the transportation sector. The significant contributions are organized as follows.

- ❖ In this chapter, first in section 2.2 we provide a background study of the Roadside infrastructure deployment strategies. Thereafter, the key research areas of RSU deployment are discussed along with the challenges in its design and implementation.
- ❖ This is followed by the discussion on the VANET routing protocols in section 2.3 and their evolution from MANET routing protocols to geographical routing technologies. Following this, we provide a brief overview of the feasibility of bio-inspired methodologies in VANET. Finally, the potential design challenges are discussed.
- ❖ Further, considering the applications and challenges of ITS we discuss existing works in the context of congestion mitigation, environmental pollution, and path planning in section 2.4.
- ❖ Lastly, we give a detailed outline of resource allocation schemes in the Cellular Vehicular-to-Everything (C-V2X) communication paradigm in section 2.5. Resource allocation in C-V2X, especially in Mode 4, is a crucial area of research as it directly affects system performance in terms of reliability, latency, and efficiency.

This organized background review set up the base for the subsequent chapters, delivering the required foundation to analyze the challenges and proposed solutions in vehicular communication and ITS.

2.2 Optimal deployment and operating strategies of roadside units in VANET

Due to the dynamic vehicular node density, high mobility and limited computational ability V2V communication is less reliable and unstable. Deploying a roadside infrastructure is a feasible remedy to disseminate information efficiently. It is vital to place them intelligently at crucial points so that the maximum number of vehicles can be attended to in a budget friendly way. To preserve network resources and use them intelligently RSUs tend to operate in an on/off scheduling manner where they can perform according to the essential situation needs.

2.2.1 Deployment of roadside units in VANET: Overview of RSU deployment Strategies

Substantial literature survey is conducted in this section regarding the optimal RSU deployment schemes, which is an integral component of the ITS networks.

Varying vehicular density influences the transportation network. Barrachina et al. [25] propose a density-based RSU placement strategy, which considers the fact that vehicular density is not the same for each road length. Here, RSU deployment is inversely proportional to vehicular density. In the case of dense areas, vehicles can communicate among them and control the traffic. On other hand for sparse areas, RSUs have to take responsibility, as there is a lesser number of vehicles. The major challenge with this work is that in absence of optimal RSU placements, centralized regulation schemes such as traffic forecasting, congestion avoidance, etc. are very difficult to implement.

Complementarily, Yu et al. [26] propose an optimized RSU placement model based on traffic demand. They have observed the delivery delay performance of VANET for different traffic densities. Although they have utilized simulation data through their model, delivery delays are reduced, and more vehicles can be served.

Saad et al. propose [27] a machine learning-based approach where RSU is placed only in dense traffic areas is the next noteworthy work. The LSTM model is used to predict the traffic density of a region from the vehicle information database. The primary concern for RSU placement is to ensure enhanced QoS.

Another remarkable research is explored by Liu et al. [28], where the entire delay of broadcasting warning messages in VANETs across highways in the form of clusters that can communicate with each other within two hops. When clusters lose communication, messages are passed through vehicles until they find an RSU. Relationships between traffic flow density, transmission range, and delay are calculated to get the optimal number of RSUs. However, optimally deploying RSUs has not been explicitly dealt with in this work.

Further, Ahmed et al. [29] present an RSU deployment policy on a highway with reduced network delay and increased capacity. They have used integer linear programming to design the optimization problem with notable improvement in terms of QoS parameters. However, they have considered only uniform distribution and cost-effective strategy for comparison.

On the other hand, Sankaranarayanan et al. [30] designed an Optimal Roadside unit Distribution Planner (ORDP) that finds out the optimal position for RSU deployment for sparse dense, and even road segments. This system considers different road parameters and categorizes them as default and optional according to their importance based on D-Trimming Algorithm and Evolutionary Genetic Algorithm (EGA).

Wang et al. [31] observe the delivery delay of information for RSU placement. Keeping that QoS parameter in mind they have proposed a mathematical model for a sparse region where two RSUs are not directly connected. This framework considers speed, traffic density, and distance among the deployed RSUs. Due to budget limitations, it aims to place RSUs so that more locations can be covered with a smaller number of RSUs.

Wang et al. [32] incorporate the centrality concept of social networks for RSU deployment approach which is represented as Centrality based RSU deployment (CDA-DC and CC). Mainly DC (Degree Centrality) and CC (Closeness Centrality) are used to find the important location and subsequently to design RSU deployment as a linear programming problem within a fixed budget. They did not compare QoS parameters and considered only limited centrality measures.

In [33] Fogue et al. propose an effective, low-budget RSU placement scheme named the genetic algorithm-based RSU deployment scheme to mitigate signal propagation issue and delay in receiving warning notification. Simulation results show this algorithm improves emergency message delivery services for different traffic density scenarios.

Kim et al. [34] give a budget-constrained RSU deployment policy that provides three kinds of scenarios for RSU deployment namely, static positions, public transport like buses, and fully controllable moving vehicles. Here two independent stages are applied in a directed acyclic graph. In the initial one, a greedy approach is used for the maximum K coverage problem and the later one uses a greedy algorithm to solve the maximum coverage budget problem. They assume that public transportation is not affected by traffic jams or the resulting delays and that its travel schedule is known. Although this is not a practical consideration, this approach is still innovative as it provides three deployment strategies for future research.

Jiang et al. [35] propose a budget constraint RSU placement strategy where the reliability traffic flow monitoring system is increased. Traffic movement to be covered by as many as possible RSUs is the key concept of this approach.

Xu et al. [36] adapt the game theoretic approach for RSU placement. Covering the maximum number of points of interest (POI)\ through a minimal number of RSUs is the key focus of this budget-limited deployment strategy. Enhancing coverage region of an RSU is another effective approach for RSU deployment.

Cheng et al. [37] discover the geometry-based sparse coverage protocol GeoCover that targets many parameters such as geometrical attributes of roads, mobility of vehicles, and resource scarcity. It finds out important coverage areas by analyzing trace files. However, the network delay issue is not explored.

Moura et al. [38] represent the transportation network as a graph and use BC to process it such that it provides improved network coverage. They model the framework as a Maximum Coverage with Time Threshold Problem where they target to place a reduced number of RSUs to increase coverage of vehicles for a minimum RSU-vehicle contact duration. BC is used to pre-process the graph then it is fed to the genetic algorithm. Therefore, the search space region is minimized for the algorithm. It provides better vehicle coverage in comparison with greedy-based approaches.

Wang et al. [39] consider both a smaller number of RSUs with more coverage to implement an efficient RSU placement policy. Multi-objective differential evolution algorithm is used to achieve the goal. Popular intersections are considered the best promising locations for RSU deployment.

Guerna et al. [40] address the cost issue of RSU deployment, and their algorithm reduces the number of RSUs to an optimized level, balancing cost and coverage efficiency. They have used bio-inspired ant colony optimization that finds more popular intersections. The authors have compared the results with varying transmission ranges, budgets, and the number of RSUs. However, the scenario is not validated in the real-time urban environment.

Babu et al. [41] provide a new metric Effort for RSU deployment in a 5G-enabled VANET environment. It considers the effect of the length of the road, type of road, and junction's importance based on the users' trips. An effort graph is generated with the help of a road network to select RSU positions through Effort Betweenness Centrality (EBC) to enhance vehicle-to-RSU connection.

Mao et al. [42] propose an RSU placement scheme based on intersection popularity. This popularity index is calculated based on three metrics, the first one is vehicle contact time, the second one is intersection connectivity, and the last one is intersection coverage capacity. An improved hotspot discovery algorithm (IHDA) is used to decrease interference between neighboring RSUs by introducing an inhibition distance between them. A realistic road environment is selected for performance analysis based on packet delivery ratio (PDR), contacts per trip, end-to-end (E2E) delay, and coverage time ratio.

Chi et al. [43] target to place RSUs at the prioritized intersection points. They have considered three optimal methodologies such as greedy, dynamic, and hybrid. Real-time transportation maps are used to search optimal locations for RSU deployment along with real-time traffic data.

Lamb and Agrawal [44] investigate the significance of a particular region through the GPS data fetched from smartphones. By analyzing the gathered data, the most common places traveled can be recognized. Through this statistical analysis, the most visited intersections are identified. RSU deployment in those intersections covers the regions and reduces the establishment cost. Table 2.1 revisits the state-of-the-art RSU deployment frameworks concisely.

Table 2.1: Summarizing existing RSU deployment strategies with achieved goals

RSU Placement Strategies	Existing Works	Goals achieved
Vehicle density-based	[25] RSUs are placed in sparse regions where adequate vehicles are not available for communication	The number of required RSUs is less and accident notification time is reduced in Madrid city.
	[26] RSUs are deployed based on traffic demand. Delay performance is considered for optimized placement.	Delivery delay is reduced, and more vehicles are assisted.
	[27] A machine learning model is used to predict traffic density and a dense traffic region is selected for RSU deployment.	Performance is evaluated by real time on road vehicles improving QoS.
QoS performanc e-oriented	[28] Default and optional road parameters are categorized to form an objective function that uses the Fusion algorithm and Genetic algorithm	RSU placement is in sparse, rural and highway areas of Tiruchirappalli city of India providing better coverage
	[29] Integer linear programming-based optimization is designed for RSU placement in highways.	Achieves reduced network delay and increased capacity.
	[29] Broadcasting delay of alert messages is considered for VANET clusters. Relationship between optimal numbers of RSUs with distance is established.	Broadcasting delay is analyzed with respect to transmission range.

Budget Constraint schemes	[30] DC and CC are used to detect important positions for RSU placement. A fixed budget linear programming model is introduced	Coverage time ratio is increased
	[31] Genetic-algorithm-based budget constraint RSU deployment model is introduced that targets signal propagation issue and delay in receiving warning notification	Emergency message delivery is faster for different traffic density scenarios.
Traffic Coverage based	[35] Geometry-based sparse coverage protocol GeoCover targets road geometry, vehicular mobility, and lack of resource. SUMO trace files are used to search critical traffic coverage regions.	Improved PDR and reduced loss for Ottawa city-based traffic simulation.
	[37] multi-objective differential evolution algorithm is designed to achieve a smaller number of RSU with more traffic coverage.	Convergence speed of proposed algorithm increases in comparison with evolutionary algorithms. Coverage area is enhanced with a smaller number of RSUs.
	[36] Transportation network is represented as a graph and BC is utilized to enhance network coverage.	Urban and sub urban areas of Switzerland is considered to cover larger region with a smaller number of RSUs.
Intersection /Junction popularity based	[38] ACO optimization is used to find out most popular intersections for RSU placement.	Achieves better area coverage, overlapping ratio and reduced number of RSUs.
	[39] Road length, type and junctions' importance are used. Betweenness centrality is considered for RSU placement that improves V2I connection.	Contacts per trip and PDR are enhanced with enough contact time and contact probability. Indian cities with unplanned and planned structure are considered for simulation.
	[42] Utilizes GPS data to identify most travelled intersections. RSUs are placed on those intersections.	RSU area coverage is increased which significantly reduces establishment cost

2.2.2 Intelligent operating frameworks of RSUs

Next-generation vehicular networks demand high data rates, ultra-low latency, complex data analyzing, and data transferring capabilities. These requirements are not met by conventional vehicular short-range communication and LTE. However, 5G-enabled and battery-powered RSUs are already emerging as integral components for the future generations of Intelligent Transportation Systems (ITS). Laha and Dutta [45] proposed an intelligent and energy-efficient on/off scheduling of mm-Wave beams equipped with RSUs based on current traffic conditions. This intelligent linear programming formulation of optimal RSU operation is a remarkable solution to preserve network resources. Further, Laha and Dutta proposed another energy-efficient RSU on/off scheme. Urban traffic follows a predictable pattern and is used here to dynamically operate RSUs. The deep Q-learning method is used to predict traffic and according to that, RSUs are switched on or off, minimizing energy consumption. A city map is used for simulation in SUMO [46] for both works. Zhang et al propose a heuristic scheduling protocol called Multi-Level Greedy (MLG) based on mixed integer non-linear programming to determine optimal and suboptimal service positions to get the RSU On-Off matrix [47].

- Thus, it is inferred from section 2.2 that multiple unique challenges and constraints still need to be focused on for RSU deployment. The primary requirements of RSU deployment are to provide connectivity and reliable transfer of traffic information from vehicle to RSU while satisfying the strict QoS needs. While for backhaul transmission, the primary concerns are low latency and complexity. Drawing from this insight, in the next section we study VANET routing algorithms for packet transmission, which can act as an enabler for several ITS applications. The algorithms facilitate communication and data transfer between vehicles, infrastructure, and other elements, which is essential for applications like traffic management, safety systems, and real-time data sharing in ITS.

2.3 VANET routing protocols: From overview to limitations

To establish the significance of the proposed research, we have studied and reviewed a good number of available literatures. Routing protocols are mainly categorized into topology-based routing protocols and geographic routing protocols. The first one utilizes network topology information to connect vehicular nodes, and another one incorporates location-based services to route the data packets in the network [48]. Nature-inspired meta-heuristics algorithms are widely used to generate QoS-aware optimal routes for the VANET environment because of their self-organizing nature. The motivation behind exploring bio-inspired algorithms is discussed in Chapter 1 section 1.2.

2.3.1 Topological and Geographical VANET Routing Protocols

Conventional topology-based routing protocols were implemented for MANETs to be integrated with VANET due to their distributed and self-organizing nature. As VANET has to deal with rapid node mobility, conventional topological models are not suitable. Before data transmission, the primary step is to discover the topological route from source to destination. Routing protocols can be either reactive or proactive, depending on the route formation mechanism. Proactive routing protocols are table-driven, where vehicular nodes periodically transmit hello packets to discover and maintain information about their neighboring nodes. Instances of proactive routing protocols are optimized link state routing (OLSR), and destination-sequenced distance vector (DSDV) [49] [50]. Reactive routing protocols detect routes whenever it is necessary to send a packet from source to destination. Several protocols like ad-hoc on-demand routing (AODV) and dynamic source routing (DSR) fall in this category [51] [52].

Researchers used AODV largely and modified it to enhance its applicability in the VANET environment. In [53], Yuan et al proposed an ad-hoc on-demand multipath distance vector (AOMDV) that discovers multiple routes from one time route-discovery process. It advertises the hop count of nodes from source to sink and creates independent links to join the nodes. When a particular link has broken the entire path is still functional because of the multiple independent links.

In [54], proposed by Junior et al, AODV is used to deliver a new routing protocol denoted as priority ad-hoc on-demand multipath distance vector (P-AOMDV). It uses public buses to form a mobile backbone network that improves network connectivity. It generates multiple routes between source and destination and provides a clear vision of the network.

Geographic location-based routing protocols are most applicable and settled for random and highly mobile vehicular environments. It utilizes location identification methods by Global Positioning Systems (GPSs) to transfer the data packets to the next neighbor. Basic greedy approaches like Greedy Perimeter Stateless Routing (GPSR) and Greedy Perimeter Coordinator Routing (GPCR) use present geographic location acquired from GPS receiver to search next hop delivery node by periodic beacon messages [55]. Aldahlan and Fei [56] proposed a novel geographic routing methodology and applied NDN (named data networking) in vehicular networks with Delay Tolerant Networking (DTN) assistance, named GeoDTN-NDN. One threat of incorporating NDN in VANET is the potential for flooding issues related to interest forwarding, data forwarding, and delivery. Additionally, these processes may encounter disruptions due to the rapid mobility of vehicles. This strategy took geographical routing to challenge flooding issue of interest forwarding and the disruption issue of data forwarding in NDN. It deduced a hybrid geographic routing technology with controlled greedy, perimeter, and DTN modes in packet forwarding. For performance evaluation, this method is compared with conventional Vehicular Inter-Networking via Named Data Networking (V-NDN). A hybrid geographic routing solution that deals with both interest forwarding and data delivery gives better results.

Rana et. al. proposed an opportunistic routing algorithm denoted as Opportunistic Directional-Location Added Routing (OD-LAR) protocol, which utilizes full broadcast characteristics. It is a combination of position, link quality, and angular deviation. These three-routing metrics prioritize the next-hop packet forwarder nodes at the boundary area of the routing search space toward the destination node. The proposed protocol **OD-LAR** gives the highest weightage to **the** node that has the minimum distance from the destination, good link quality, and minimum angular deviation and assigns it as the best candidate for the next hop forwarder node. The primary goal of the OD-LAR is to reduce packet overhead, packet drop rates, delay, and increase throughput. For performance study, this approach does not consider any traffic simulator and compares the routing metrics with only variations of location aided routing (**LAR**) protocols that may not be practically feasible from real-time perspective [57].

Qureshi et al propose RAGR (road aware geographical routing protocol) that applies suitable routing metrics distance, direction, and traffic density as the selection parameter to choose the next vehicle for data transmission on the way to the destination. RAGR follows two methods for stable data forwarding: one when the vehicle is on a road section and the other when the vehicle is at an intersection. For the first scenario, the next forwarder vehicle is selected based on distance and direction. For the later one the next route is selected based on curved metric length and traffic density. As the protocol relies on traffic and road conditions, it suffers from packet drop and unnecessary retransmission that degrades its performance [58].

2.3.2 Remarkable Bio-inspired VANET routing Protocols

Some notable algorithms from this category are elaborated further, which are useful in enhancing the performance of VANET routing QoS parameters. Proposed approaches are illustrated in the contributory Chapter 4.

Rana et al proposed mobility-aware zone-based ant colony optimization routing for VANET (MAZACORNET) in [59]. This approach follows the vehicle's mobility pattern, velocity, density, and fading conditions to create multi-path ant colony optimization-based routing. ACO searches several routes between source to destination to avoid link failure. To make the network scalable it is divided into different zones that eliminate congestion. ACO is utilized to design a routing optimization algorithm whereas pheromone is mapped as a combination of link quality and successful packet receiving probability. Route discovery is done for both the intra-zone and inter-zone scenarios.

Srivastava et al. proposed route discovery using the ACO algorithm (RDACO), which explores all possible paths for data transmission. Among these paths, the most stable one is selected for final routing. While this makes the protocol reliable, it also increases overhead. Since all vehicles are considered for route discovery and forward ant packets, this leads to higher routing overhead. In the next phase, backward ant packets maintain the discovered route. Traffic density variation affects the performance of RDACO, as more vehicles result in a higher number of control packet broadcasts [60].

Datta et al merged the conventional routing protocol AODV with ACO and named it ant-AODV-VANET. It includes movement data of vehicles at the time of route discovery. The route with the shortest length and highest link quality is selected for sending the packet. According to the performance analysis, the discovered route is the most accurate and stable [61].

Li et al proposed another protocol and named it vehicular routing protocol based on ant colony optimization (VACO). It is a combination of proactive and reactive approaches to generate and sustain routing paths respectively. It assumes every intersection is placed with RSUs, which provides periodic relaying capacity of roadways. ACO is used to determine paths between sources to destinations through the intersections. Pheromone routing tables decide stochastic routes at every junction. Although it provides satisfactory QoS performance in comparison with geographical routing the design parameters are still limited. Another issue is that RSU deployment at each junction can be expensive and this eliminates the adaptability of meta-heuristics algorithms [62].

Another good work was done by Goudarzi et al which is the enhanced version of geographical source routing called enhanced geographical state routing (EGSR), solely designed for city environments and follows ACO. In this framework, vehicles are always equipped with digital maps, which make them aware of the roads and street conditions. Ant control packets discover routes according to network connectivity. This protocol is based on road conditions and congestion without mobility consideration. EGSR requires less traffic infrastructure such as RSUs and sensors as a particular junction can take care of a certain amount of anchor area [63].

Ramamoorthy et al. challenge the ad hoc nature of the VANET environment. Their target is to find energy efficient congestion-free shortest routing path. This algorithm uses ACO and pheromone level, which depends on the link's fitness value. It considers distance, residual energy, and congestion level to determine the pheromone concentration. The routing path follows the link that has the highest fitness value, which also gives the shortest and less congested path. This algorithm outperforms in comparison with other ACO-based routing algorithms such as fuzzy-based ant colony optimization (F-ANT), improved distance-based ant colony optimization routing (IDBACOR), and ant colony optimization routing algorithm (ARA) [64]. In [65], Husain et al proposed three different PSO-based geocast routing protocols and named them LARgeoOPT, DREAMgeoOPT, ZRPgeoOP. These protocols are adaptable and scalable in a rapid VANET environment because of the consideration of routing loads.

They have shown improvement in terms of packet delivery ratio (PDR), delay, routing load, and throughput.

Yelure et al uses the distance and speed of the vehicles to determine the next forwarding vehicle in their proposed work. They have used particle swarm optimization to implement QoS-enhanced VANET routing PSOR. Although the protocol shows better performance in comparison with the variants used, still it is not implemented in a realistic city environment where two lanes or four- lanes are part of the network [66].

In [67], Gnanasekar et al proposed a cost function to resolve vehicle routing issues based on network quality parameters such as congestion, collision, and QoS awareness. It determines the optimal route with minimal routing cost by the novel algorithm called mean computing Jaya algorithm. Fuzzification of the QoS metrics is also done by assigning numerical values to the metrics. The result is compared based on cost analysis and convergence analysis with PSO, Jaya, and GWO.

Joshua et al proposed a novel routing protocol for VANET and called it a reputation-based weighted clustering protocol (RWCP) which uses a multi-objective firefly algorithm (MOFA) for optimization. The protocol is organized by considering the direction, location, speed, number of neighbours, lane ID, and each vehicle's reputation. MOFA is assigned routing parameters as input which targets achieving increased cluster lifetime, PDR, and reduced overhead. Vehicles form clusters and reputation is set according to the number of times a vehicle is elected as cluster head. CH performs the beaconing and packet-forwarding task periodically and informs other members about the time-out status. Fireflies are used as the distance is proportional to the light intensity, which is a key factor in making vehicle clusters according to their brightness [68]. Although the protocol is implemented in the real-life map and traffic mobility is generated in SUMO they depend more on CH vehicles. In a dynamic network, it is difficult to make the same node as CH repeatedly. If link breakage occurs, then the cluster members stop receiving Hello messages from members. In [69], Kasana et al proposes a novel geographic routing (GR) protocol that follows cat swarm optimization (CSO), denoted as CSO-GR. A fitness function-based optimization is utilized to select next forwarder vehicle. CSO is a meta-heuristic algorithm that incorporates ACO and PSO. It motivates from the hunting skill of cats. The fitness function is modelled to find optimal distance to target, vehicle mobility, available bandwidth and degree of the next neighbouring vehicle. Performance is studied through simulation and CSO-GR outperforms in terms of PDR and routing load. Figure 2.1 illustrates the classification of VANET routing algorithms and a brief overview of significant VANET routing protocols is presented in table 2.2.

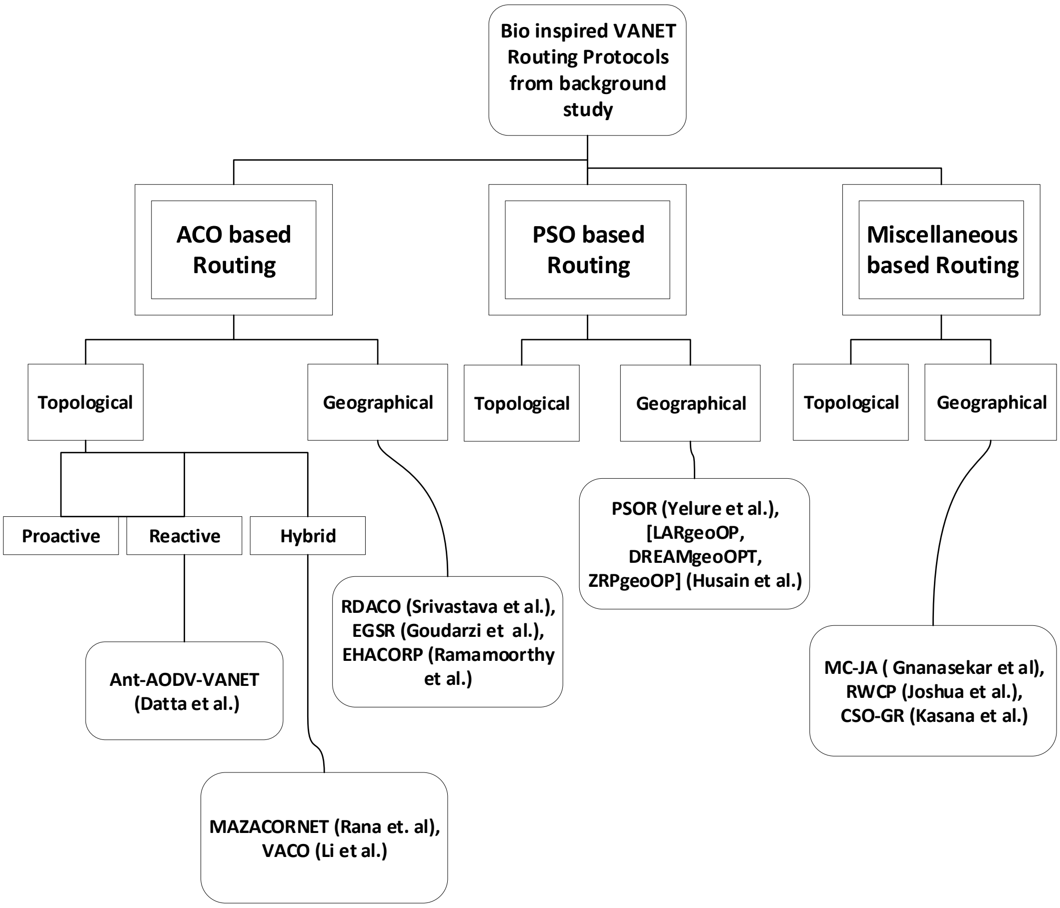


Figure 2.1. Classification of bio-inspired VANET routing protocols.

Table 2.2. Comparison of significant VANET routing protocols

Reference	Scheme	Basic Design	Advantages	Issues need to be addressed
59	MAZACORNET	Vehicle's trajectory, flow, speed and fading scenario is utilized to implement ACO based routing.	Performs well in dense network. Multiple routing path created QoS achieved in terms of better PDR, delay.	Route maintenance and discovery increase overhead. Communication between zones is a challenge.
60	RDACO	Finds all possible paths for packet transmission, most stable route is selected among them	Overall achieve better PDR, throughput, delay	Routing overhead is not considered
57	VACO	Adapts both reactive and proactive approach to provide and maintain best route.	Average delay, Average delivery ratio and overhead is considered and improved.	Realistic vehicular environment is not considered.
58	Enhanced hybrid ACO routing protocol (EHACORP)	Calculates distance between vehicular nodes and selects the shortest path to send data packet	PDR, delay, throughput and packet loss rate is compared and outperforms with reference algorithms	In rapid VANET environment, shortest path is not always the stable one. Link stability and alternate routes are not considered.

59	LARgeoOPT, DREAMgeoOPT, ZRPgeoOP	PSO based geocast routing is used to explore optimize path for packet transmission.	PDR, throughput, delay, Routing load and dropped packets ratio is considered for QoS improvement.	Comparison with reference routing protocols is not enough. Only traffic density variation is considered.
61	PSOR	Speed and distance are measured to select next forwarding vehicle	Utilization of higher packet size results in better message delivery ratio, throughput and lesser delay	One lane is observed for routing. Two lane or four lane roads need to be covered for real time traffic scenario.
62	MC-JA	Collision, congestion, travel time and QoS are used to establish the cost function. Fuzzification is included in routing cost.	Optimal route with reduced collision, congestion and increased QoS are achieved.	Performance is not compared with benchmarked VANET routing algorithms.
63	Reputation based weighted clustering	Direction location, speed, number of neighborhood vehicles lane id and each nodes' importance are utilized as input in multi objective optimization scheme	Neighboring vehicles form cluster and their lifetime are increased with reduced overhead. PDR is improved in comparison with PSO based algorithms.	Link maintenance between clusters can be challenging in rapid vehicular network.

Concisely, the aforementioned works have targeted performance improvement of VANET routing and efficient packet forwarding. However, attention is required to one or more of the following that generate our motivation behind the proposed routing protocol in this thesis included in Chapter 4.

❖ In urban environments, vehicles often move in clusters with relatively uniform speeds, especially during organized traffic conditions like controlled intersections or dedicated lanes. This behaviour is supported by urban traffic flow dynamics studies, such as cellular automata traffic models and clustering methods for traffic flow patterns [70], [71]. When the source and destination pair in a vehicular network has previously exchanged packets, route discovery can be avoided using cached route information. Roadside Units (RSUs) are highly efficient for transmitting route information and disseminating data due to their static positioning and high bandwidth capabilities [72]. Moreover, RSU caches can store stable route information for a specified time, reducing the need for frequent route re-discovery [73]. Vehicles can utilize this cached data for packet forwarding, minimizing delay and communication costs compared to relying solely on moving vehicles. This thesis incorporates this approach in VANET routing that utilizes RSU caching, as detailed in Chapter 4, Section 4.3, significantly reducing network overhead and improving overall performance.

- ❖ Rapid changes in the scenario significantly affect the VANET environment. While the literature in this area is limited, we have considered the effects of varying factors such as the number of vehicles, maximum vehicular speed, data packet size, and source-to-destination distance on the performance of four key QoS metrics: Packet Delivery Ratio (PDR), latency, throughput, and overhead. This clear comparative analysis strengthens the result analysis by providing a more comprehensive understanding of these influencing factors.
- ❖ Another motivation behind the proposed routing protocol is to reduce the large number of control packets generated for route discovery and maintenance. In traditional methods, each vehicle in the hop broadcasts control packets, which consumes bandwidth. This research introduces a methodology with fewer control packets—specifically, a single packet. Whenever a vehicle receives a control packet from its current hop, it restricts further broadcasting, thereby conserving bandwidth.

Based on our understanding, no existing research in the literature has collectively addressed these concerns. This highlights the novelty of the algorithms proposed in this thesis. It can be deduced from this section that VANET communication poses unique challenges and constraints. Furthermore, when application-oriented studies are conducted using VANET routing and optimal infrastructure deployment technologies, the specific requirements of these applications must also be carefully considered.

2.4 ITS Applications: Prospects and Overview

- ➢ As already discussed in Chapter 1, purposes that are more precise are to reduce congestion, utilize the road resources at the maximum and provide lower levels of fuel consumption and CO_2 emission. At the same time, considering the immense importance of ITS for personalized destination searching, supporting the fastest path planning under congested traffic conditions is an imminent requirement. Therefore, these areas of ITS demand meticulous background study of existing implemented research and their encountered challenges. Accordingly, the next section of the thesis discusses the relevant literature.
- ➢ Initially, we accounted for the notable works based on the implementation of variable speed limiting systems. Roads with static speed-limiting systems fail to provide reliable

traffic management systems and create unnecessary congestion. This motivates us to implement a variable speed limiting system to display appropriate speed limits according to real-time situations.

- Following from that focus shifts towards designing efficient path planning as it is necessary to improve traffic throughput in terms of less travel time and increased vehicular speed. Our objective is not only providing the fastest path but also suggesting the most convenient destination according to the present condition. Keeping that aim in mind extensive literature review is conducted about the recommendation systems.
- Lastly, the review segment considers the existing works that concentrate on the minimization of fuel consumption, CO_2 emission and travel time.

2.4.1 Significant variable speed limit systems for congestion control

To resolve traffic jams one frequently applied traffic control scheme for urban freeways are variable speed limit (VSL) systems. The incorporation of VSL in intersection management can mitigate accumulation of traffic at intersections, which ensures smooth traffic flow among intersections. Several algorithms are designed to decide appropriate VSL values.

Yang et al provide a proactive VSL system for freeway work zones. Optimal speed limits are imposed based on predicted traffic states. Where detectors are not available, Kalman filter is used to generate the prediction results. For the sake of operational safety, a new control objective is included to ease the speed reduction phenomena throughout the target freeway. A feedback function is also incorporated in the control system that considers drivers' compliance rate. Simulation setup is built on VISSIM that simulates traffic for both upstream and downstream road segments. This system effectively decreases speed for upstream to a downstream to resolve congestion generated in the freeway [74].

Han et al. propose a swift model predictive control (MPC) scheme to implement VSL that minimizes traffic jams. MPC is designed based on an expanded discrete first-order model that considers the capacity drop of jam wave. For the performance study, system is applied to a standard freeway stretch to observe computation speed and jam wave clearance [75].

Khondaker and Kattan propose a VSL system that concurrently enhances the mobility, safety and environmental issues in a Connected Vehicle scenario. This microscopic approach accounts drivers' pattern their acceleration, and deceleration using the MPC. Traffic flow is predicted to measure total travel duration and safety time to avoid collision along with environmental impact consideration. Drivers' experience is used to set optimal speed limit. Simulation result exhibits that the system performs well in terms of safety, mobility and sustainability. This approach solely depends on the connected vehicular environment and does not consider the noisy medium and delay of wireless medium, which is not practical [76].

He et al. addresses the impact of vehicular speed on greenhouse gas emissions and fuel consumption. Numerous studies have suggested optimal speed advice for drivers, but they fail to account for the effects of queues at intersections, which makes their solutions infeasible in real-world scenarios. To address this issue, a multi-stage optimal control framework is proposed that considers both traffic light timings and vehicle queue updates to determine the optimal vehicle speed trajectory. A constrained optimization formulation is used as an approximation strategy, allowing for faster solution times. Although simulation results highlight the significance of the model, the speed advisory system still relies on accurate estimation of traffic light and signal statuses. Additionally, individual vehicles' advised speed can impact nearby vehicle platoons' performance, leading to unavoidable delays and increased fuel consumption. Therefore, a systematic perception of traffic flow should be incorporated, rather than focusing solely on individual vehicle speed control [77].

Yu et al propose a variable speed limit system in a connected autonomous vehicle (CAV) scenario for a freeway corridor with several bottlenecks. This strategy uses extended cell transmission model (CTM) that considers multiple factors like capacity reduction and mixed traffic flow, along with conventional cars, heavy vehicles, and autonomous vehicles (AVs). A multi objective function is formed aiming to make the operation fast and increase the smoothness of the speed transition. A genetic algorithm (GA) is used to solve VSL control problem. A real-world freeway is taken to evaluate the designed control framework. Sensitivity analyses is done to understand the effects of both the penetration rate of CAVs and communication radius. Simulation results revealed that this VSL control not only increases the overall efficiency but also decreases the experimental region tailpipe’s emission rate. The simulation also shows that the VSL control incorporating vehicular communication such that vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and infrastructure-to-vehicle (I2V) delivers better results rather than the VSL control only [78]. These significant frameworks motivate us to explore the RSU-controlled VSL system in our contributory work in Chapter 5.

2.4.2 State-of-the-art path planning systems for congestion control

Looking forward to our further findings, Intelligent Transportation System has enormous applicability in transportation management and control. Applications like mapping services provide real-time traffic information and navigation, but they do not offer customized routes or consider user preferences. An ITS-based recommendation system is required to address the issue. Recommendation systems are immensely popular nowadays to generate customized guidance or services to the users on basis of their circumstances and preferences. Precisely, an algorithm advises exact suggestion to users [79]. Using these schemes online video platforms advice movie recommendation to viewers and e-commerce websites shows relevant products to a dedicated customer base [80].

In literature study, recommendation system has huge applications; determining reliable healthcare destination at the time of emergency is one of them. We have found several remarkable works in literature. In [81] Khoie et al surveyed patients' satisfaction factors. This unsupervised information is used to make patient communities and understand their preferences that make hospitals places that are more suitable for patients. In [82], a Hospital Queue recommendation system (HQR) is proposed. They have predicted treatment time and considered the waiting time. This scheme provides efficient treatment plan for the patients. In [83], Gupta et al. design a smart ambulance system where Google API guides to provide shortest route for finding nearest hospital and monitors patient status through a central database. In [84], proposed by Habibi et al, multi criteria decision-making system TOPSIS and Multi Objective Optimization based on Ratio Analysis (MOORA) is utilized to arrange the hospital ranking. This work lags in real time implementation and route guidance. In [85], proposed by Choudhury et al, a hospital recommendation is supplied based on neural network. They have designed a web application but not provided any route planning.

In view of the shortcomings raised by the literature above, we develop a hospital recommendation system with an optimal path planning facility in Chapter 5 that assesses the users' requirements and accordingly advises the destination and its route.

As per the mentioned objective in section 1.2, noteworthy route planning frameworks that contributed to advancing this work toward congestion mitigation and the minimization of fuel consumption and CO2 emissions are summarized further. Pan et al. proposed a centralized infrastructure to obtain real-time vehicle speed, direction, and geographic positions for traffic congestion detection. After detection, vehicles are rerouted according to two different algorithms. The first, Dynamic Shortest Path (DSP), routes vehicles based on the shortest paths and lowest travel time. The second, Random k Shortest Paths (RkSP), selects a random route from among the k shortest routes. The second approach balances the re-routed traffic among several paths, whereas the first approach may cause congestion on alternative routes and does not fully account for the real-time traffic scenario [86].

Brennand et al. proposed an ITS that detects and controls congestion for urban environment where distributed RSUs provide total coverage of the city. Here RSUs are placed in distributive manner, which generates traffic control operation according to real-time traffic data and only considers its respective coverage area to manage and detect congestion. Congestion control is achieved through the periodic re-routing of vehicles to avoid congested routes. However, this reactive approach is not capable of detecting congestion immediately as it occurs. System successfully produces less CO_2 emission, fuel consumption and travel time. Although this approach provides better performance, still RSU dependency makes this model unrealistic as RSU deployment itself is a budget-limited task [87].

Souza et al. presented an intelligent methodology named CHIMERA (Congestion avoidance through a traffic classification mechanism and a Re-routing Algorithm). It assumes congestion at the time of its occurrence and distributes the traffic in such a manner that in near future traffic congestion can be controlled smoothly. KNN algorithm is used to differentiate congestion levels from high to low based on the input parameters such as average vehicular speed on the road and traffic density of the road [88].

Paul and Mitra provided a fog computing-based vehicle-rerouting algorithm. It assigns a cost to decide the next forwarder point. Vehicles communicate with fog components, which are further attached to central server. This scheme diverts the vehicles encountered by some unexpected event to avoid congestion and considers the green signal timing of a lane for designing the methodology. Algorithm supremacy is established by comparing it with Dijkstra and A* [89].

Sumon and Jaekel introduced a dynamic route-planning scheme that used present traffic scenarios to plan vehicle trajectories. Traffic management centers, RSUs, and OBUs are the main functional components through which fuel-efficient route planning is established. Vehicles encountered delay at the time of travel, which is used to calculate the cost function of each travel path and lowest cost route. They used fixed delay threshold and traffic light timing, which made the approach infeasible [90].

The next remarkable work is approached by Li et al., which introduced vehicle-to-cloud connectivity (V2C2V) for route planning and also considered safety parameters. Roads are evaluated based on accident and risk frequency database, which is used to predict risk factor by hybrid neural network. Features like peak hour of the day, weekday or weekends and weather conditions are included in the prediction model. Multi objective network problem is implemented based on risk factor and expected travel time. To plan the best and safe route real world scenario of Columbus city, Ohio is used [91].

Furthermore, Guo et al. propose novel contribution in this domain that considers real time traffic data to model urban traffic scenario. The scheme estimates travel time from origin to goal location based on real time traffic data sharing between RSUs in a distributive manner, which ensures less computational cost, and redundancy. To validate the significance of this dynamic path planning they compare this with static path planning algorithms. As vehicular communication is prone to link failure and deployment cost of RSUs are very high, only RSU based distributive architecture is less practical for vehicular network [92].

Another notable work is introduced by Yang et al. named SG-ITS where SG stands for speed guidance which directly impacts driving behavior. Drivers can reach intersections during active green lights, minimizing their waiting time. They focus on the reduction of fuel usage and emission of nitrogen monoxide, carbon monoxide, particle number and nitrogen dioxide. The target is achieved by controlling the recurring start and stop and fluctuations of acceleration parameter of vehicles. The uniqueness of this work lies in the fact that they have considered both heavy-duty diesel truck and light-duty gasoline car [93].

Li et al. suggests an outstanding route planning methodology that is based on the meticulous understanding of road structure and experienced drivers' route choice. When most of the vehicles follow general shortest or fastest route then it enhances the tendency of traffic congestion. To encounter this issue, a double rewarded value iteration (VIN) based learning knowledge is adapted in route selection. Historical trajectory dataset is used to obtain global traffic conditions and route choice of experienced drivers. LSTM framework estimates the traffic movements and VIN builds the policy to estimate skilled drivers' route decisions by using both the forecasted and present traffic. Experimental outcomes validate that this scheme provides human-centric decision-making and less travel time [94].

Pan et al. presented noteworthy research for congestion avoidance known as DIVERT, a distributive vehicular traffic re-routing system. It implements a hybrid re-routing system, which addresses the privacy concern of drivers sharing trajectory information as well as the high computational cost of vehicle-to-central server communication. In this intelligent resource-sharing approach, the vehicles perform re-route tasks so that the load on the central server is reduced. The central server provides the global knowledge of traffic. As vehicles handle the alternative path selection process, commuters do not have to share the complete information of travel path that make sure privacy is not compromised. It is clear from the experimental results that this scheme may not perform very well in terms of travel time in comparison with centralized systems but it provides significant improvement in privacy maintenance and reduction in CPU and network load that is carried out by the server. Re-routing through vehicles can be effective in smaller regions; however, it becomes inefficient and impractical for larger regions, limiting the system's scalability [95].

Huo et al. proposed one more multi-layer clustering-based hybrid re-routing approach named CHRT. RSU, connected vehicles, and TMC (traffic management center) create the collaborative vehicular network. Vehicles form clusters to decrease communication time and overhead whereas the nearest vehicle from the center of the road section is elected as the cluster head. These clusters are ranked according to the traffic congestion status. A central server known as TMC generates the global knowledge of traffic. Vehicle clusters are re-routed according to their rank and multi metrics like travel time, CO_2 emission, and fuel consumption are considered to construct the algorithm. This system is less dependent on V2I communication, which ensures less location information revelation. CHRT provides improved system performance in comparison with the existing methods like no re-routing, DIVERT, etc. [96].

Tseng et al. come up with an incredibly remarkable re-routing strategy that uses present traffic data and accordingly sets the decisive weights of roads. System functions in a hybrid manner where both fog and cloud architectures are involved. Vehicular data is gathered and the location, speed, and direction information are utilized to set the weights determining the congestion level. Real-time traffic densities decide the road congestion level and according to that, vehicles are guided to the optimal path. Here, the system finds out the K-shortest paths based on decisive weights and road capacity. In the simulation environment, different scenarios are explored, such as where vehicles come from north to south, east to west, and in every other direction. Travel time, CO_2 emission, and fuel consumption are considered to validate the performance with existing re-routing strategies [97].

Soon et al. implemented an ant colony optimization-inspired proactive, eco-friendly vehicular routing model. Repeated start and stop give rise to fuel consumption and carbon emissions. It is important to keep that fact in mind that this system determines the path for vehicles that have more green intersections so that recurring starts and stops can be avoided. To achieve this, a hierarchical multi-layer architecture based on pheromone principles is employed. It consists of city agents, road supervisor agents, intelligent vehicle agents, and traffic light agents, all interconnected through intra-group and inter-group communication mechanisms. Traffic pheromones are decided based on real-time road density and upcoming densities are predicted using LSTM model. Both of them are used to recommend routes to vehicles according to their source and destinations choice. This pheromone-based system is evaluated for both routing within a city and routing to different city scenarios where travel time, CO_2 emission and fuel emission are compared with existing routing schemes [98].

The next observed rerouting strategy focuses on the missing data handling in the prediction model that is proposed by Chan et al. For exact traffic prediction, it is required to design the model in such a way so that there should be no missing data. The Weighted Missing Data Imputation (WEMDI) method is incorporated to manage the situation. Infrastructures use unique vehicle IDs to determine how many vehicles are unable to transmit data. During prediction, they take this into account and adjust the deep learning neural network model parameters accordingly. This helps predict transportation parameters, such as speed and traffic density, with greater accuracy. In a rapid vehicular network where link failure is a very common phenomenon, this feature increases the prediction model significance in a great manner. In result analysis, this system does not consider the existing vehicle routing algorithms, which is required to establish the supremacy of the system [99].

Zhu et al. [233] propose the next notable work that we have used for performance evaluations of our proposed scheme is named PRGM means prediction-based route guidance method. It is also a hybrid architecture and vehicles are participating as clusters with the collaboration of cloud. It takes several traffic parameters like speed, density, and acceleration to build the congestion detection model. Route guidance is provided considering the overhead of finding or changing the present route. This dynamic architecture reduces travel time and pollution generation. Although it applies a backup mechanism using nearby cluster heads to prevent data loss still cluster head formation and cluster maintenance generate network overhead, which affects the accuracy of congestion prediction.

Ho et al. [234] propose another pheromone-based approach that draws our attention, which is named Proactive Travel-time Pheromone Rerouting (PTPR). It estimates future traffic status by travel time and vehicular density to plan routes for vehicles. Unlike other pheromone-based systems, here each vehicle can contribute its pheromone on several roadways, instead of its direct adjacent path. A localized shortest path algorithm is used to direct the vehicle's route. SUMO is used to model traffic for urban and suburban areas. Here, performance parameters are mean travel time, increasing number of arrived vehicles and fuel consumption of suburban area of Woodlands and urban area of Novena.

Rezaei et al. prominently explored hybrid fog-cloud-based vehicular infrastructure in their proposed frameworks and entitled them ReFOCUS and ReFOCUS+. In ReFOCUS bigger area is divided into smaller regions and each region is assigned a fog node. Vehicles and fog nodes are connected to cloud servers to reduce the computational cost, bandwidth usage, and storage scarcity. Commuters receive the required knowledge very fast due to this cooperative arrangement. The system detects road and zone congestion and then allocates the best route for vehicles. Later one is the advanced version of ReFOCUS where a multi-metric cost function is used to measure the road condition. The metrics are traveling time, traffic flow measure, and level of congestion. System guides optimal route to the vehicles according to the real-time traffic situation. For performance evaluation both techniques use open-source road maps and measure CO_2 usage, fuel discharge and travel time with respect to existing routing methodologies [100] [101].

Table 2.3 summarizes significant route guidance frameworks for greater understanding.

Table 2.3. Summary of significant Route Guidance Frameworks

References	Architecture	Communication paradigm	Methodology	Simulation/ testbed	Performance parameters
86	Centralized	V2V V2I	Dynamic Shortest Path (DSP) and Random k shortest paths (RkSP) are used to distribute traffic among several paths that creates balanced flow.	SUMO	Average travel time, CPU time
78	Distributed	V2V V2I	RSU gathers real-time traffic data from vehicles to detect and manage congestion.	OMNeT++ 4.3 SUMO	Average travel time, CO_2 emission and fuel consumption
79	Distributed	Long range LTE/4G	Not only re-route vehicles but also considers the future effects of it and KNN is used to classify congestion level.	SUMO	Speed, travel time, waiting time, travel distance, CO_2 emission and fuel consumption
80	Hybrid	V2V I2I	System enabled fog computing and IoT analyses real-time data from vehicles to re-route them through a next hop selection algorithm.	SUMO	Speed, travel time, waiting time, travel distance, CO_2 emission and fuel consumption
81	Hybrid	V2V V2I	Real-time traffic information is used to plan route dynamically whereas delay duration at intersection is used to identify congestion.	SUMO OMNET++ VEINS	Trip time, CO_2 emission
82	Hybrid	V2C2V	A safety-based route planning system optimizes road risk factors and travel time. The hybrid neural network is used to analyze accident traffic data.	Matlab	RMSE of neural network, Travel time of optimal route

83	Distributed	V2V V2R R2R	Real-time traffic information is shared for travel time estimation for dynamic path planning.	VanetMobiSim	Travel time
89	Hybrid		Paths with a greater number of green signalized intersections are selected for travel to avoid frequent stops and fuel consumption.	SUMO	Fuel consumption, CO_2 emission, Mean waiting time, congested roads, mean travel time, excess number of arrived vehicles

The limitations of these aforementioned proposals lead us to implement an optimal real-time path planning algorithm which is an improved version of existing A* algorithm which is elaborated in chapter 6 section 6.2 as *Enhanced A* algorithm*. Furthermore, the challenges of handling large-scale traffic data are tackled by the integration of federated learning to avoid the overhead of sharing localized information with a central server, thus improving training efficiency and performance accuracy. Realizing the budget constraints of deploying RSUs everywhere, the system strategically places RSUs at influential points while relying on a central server to manage uncovered regions. RSUs control local traffic, and vehicles benefit from global learning knowledge when direct communication with RSUs is unavailable. To mitigate computational complexity, bandwidth demands, and transmission delays, the system leverages mobile edge computing for resource sharing, enabling multiple distributed RSU networks to contribute collaboratively to a global traffic model. This collaborative architecture optimizes vehicle routing to minimize travel time and environmental pollution.

2.5 Optimal radio resource allocation for C-V2X Mode 4

The rise of connected and autonomous vehicles (CAVs) has brought exciting possibilities and significant challenges to how vehicles communicate with each other and their surroundings. Various communication technologies have evolved to tackle these challenges, with Cellular Vehicular-to-Everything (C-V2X) standing out as a promising solution. C-V2X allows vehicles to communicate directly with other vehicles, roadside infrastructure, pedestrians, and more, making it essential for future intelligent transportation systems (ITS). This section explores underlying research challenges and highlights existing approaches aimed at enhancing resource allocation, setting the stage for the proposed solution in this thesis.

Chourasia et. al [102] propose an improved SPS scheme named as traffic aware-semi persistent scheduling (TA-SPS). Semi-persistent scheduling (SPS) is a resource allocation strategy rapidly used in communication systems, including Cellular Vehicular-to-Everything (C-V2X) Mode 4. Its basic target is to allow vehicles, to schedule and secure resources for periodic data transmission without requiring to request them from a central server each time. Here, model parameters like the probability of keeping a radio resource ($pKeep$) and RC is configured according to traffic density. It has considered low traffic density, moderate traffic density and high traffic density scenarios for designing the parameters. PDR performance is enhanced in this scheme compared to the traditional SPS algorithm. This model has not considered the collision probability and latency parameters as design parameters.

Another noteworthy work is done by Saad et. al [103] for aperiodic traffic in V2X. SPS performs better in case of periodic traffic whereas for aperiodic traffic vehicles are bound to select fresh resources, which leads the unplanned usage of resources. To encounter this enhanced SPS (e-SPS) algorithm is introduced where reinforcement learning is utilized. Vehicles perform as agents to adjust sensing windows adaptively according to traffic density and vehicular speed. Here also PDR is used as a performance metric compared with the traditional SPS algorithm.

Further outstanding work is proposed by Hyeon et. al [104] that considers delivery rate for a probabilistic resource re-scheduling scheme (EB-PRS). Opportunistic bloom filter-based feedback is used to acknowledge vehicles' successful message delivery. From this delivery estimation, EB-PRS selects resources in a repetitive manner. This model considers both urban and highway scenario for simulation environment where packet collision is used as performance metrics.

Next remarkable work P-SPS is done by Daw et. al. [105] for emergency vehicle's resource allocation. In this model emergency vehicles are distinguished as high priority vehicles and accordingly they have allocated higher RC values. They always get the channel resources whenever they have to transmit the CAM. This scheme also includes a complementary probabilistic collision mitigation (PCM) mechanism along with an intelligent grant removal (IGR) to reduce the possibility of collision between high priority and low priority vehicles. Simulation is performed among P-SPS and traditional SPS algorithm in highly congested traffic scenario in terms of packet reception ratio (PRR).

Furthermore, Ali et. al. [106] proposed a balanced resource allocation (B-RA) model focusing on the half duplex communication issue in V2X. Sub-frames are used in a balance manner where candidate vehicles broadcast the present resource reselection information with neighboring vehicles in advance to generate the idea about future usage of resources. Whenever RC achieves the threshold value, it initiates the distribution of next RRI knowledge to other vehicles. This scheme is able to introduce balanced sub-frame distribution, increase CAM delivery rate by reducing half-duplex problem.

Another notable work is proposed by Gu et. al [107] named as multi-agent deep reinforcement learning-based SPS (RL-SPS). Vehicles choose radio resources without the overall network information. Training efficiency of RL-SPS is enhanced by the inclusion of multi-head attention model so that vehicles can notice their neighbors' actions meticulously. Agents notice RSSIs of CSRs and accordingly local actor network picks a CSR. Simulation performance is evaluated in terms of PRR, update delay (UD) and channel busy ratio (CBR). Table 2.4 illustrates the comparative analysis of significant state-of-the-art schemes that are already discussed.

Table 2.4 Overview of existing resource allocation schemes for C-V2X

References	Advantages	Disadvantages
Chourasia et. al. [102]	MAC parameters are configured carefully to avoid resource collisions that result in reliable transmission.	The simulation study does not consider the comparison with prior existing works and parameters like delay and packet size.
Saad et. al. [103]	Aperiodic traffic handling is established based on traffic conditions.	System does not observe the delay and collision performance, which is not enough to establish the superiority of the work.
Hyeon et. al. [104]	Resources are selected probabilistically and are estimated by delivery ratio.	A message delivery rate is estimated by acknowledgment feedback, it affects network overhead and delay.
Daw et. al. [105]	Prioritize emergency vehicles and provide them with a higher reselection counter so they can send CAM whenever they want.	Comparison with existing works along with delay and collision considerations are not included.
Ali et. al. [106]	Balanced utilization of sub-frames is beneficial to mitigate the half-duplex problem.	Only the CAM delivery ratio is taken as a performance evaluation metric that is compared according to number of vehicles.
Gu et. al. [107]	Reinforcement learning is utilized to select resources along with reduced collisions.	Although the system is robust, reliable, and scalable subsequent consideration of RC and resection probability is required.

Existing resource allocation methods in C-V2X Mode 4 often face issues like packet collisions, high latency, and unreliable links, which disrupt URLLC communication. To address this, forming clusters among vehicles traveling in the same direction and speed provides enhanced coordination. By electing a Cluster Head Vehicle (CHV) based on stability, resource allocation can be managed more efficiently, minimizing collisions. Incorporating a Q-learning algorithm allows the CHV to adapt sensing times dynamically to traffic conditions, reducing delays and overhead. Prioritizing latency and reliability in resource allocation ensures robust communication, addressing key gaps in existing solutions. This work is illustrated in

Chapter 7 which is driven by the goal of creating a low-latency, collision-free resource allocation framework for safer and more efficient transportation systems.

2.6 Summary of Literature Survey and Identified Research Gaps

Table 2.6 summarizes the categories of the literature survey, emphasizes the critical research gaps, and demonstrates how the thesis contributes to effectively handling these concerns.

Table 2.6 Literature Survey Categories and Research Gaps

Category	**Focus Area**	**Issues need to be focused**	**Research correlation in this thesis**
Infrastructure deployment strategies	Optimal placement according to cost-effectiveness, and coverage maximization.	I. Influence analysis of crucial points based on changing traffic patterns, and geographical significance. II. Lack of application-oriented framework	1. This thesis addresses dynamic traffic patterns and their geographical significance in complementing infrastructure placement in urban environments. 2. A traffic prediction application is used for performance validation
VANET Routing Protocols	High mobile vehicular environment, Link failure scenarios, Bio-inspired approaches	Broadcast storm scenario due to excessive control packet forwarding, Poor routing overhead due to route discovery of ACO-based algorithms,	1. An improved ACO-based routing protocol RRO-ACO is proposed. 2. The route discovery overhead of ACO is reduced using a novel routing protocol CORFA.
Applications and Challenges in ITS	Congestion mitigation, environmental pollution, path planning	Lack of real-time decision-making for path planning, Insufficient focus on integrating congestion mitigation with communication systems	1. Customized path planning is proposed. 2. RSU and cloud-based system incorporated with federated learning is induced for congestion control and pollution mitigation.
C-V2X Resource Allocation	Semi-persistent scheduling (SPS), cluster-based methods, machine learning approaches	High packet collisions and half-duplex constraints, Inefficient handling of high-density scenarios, Limited scalability for diverse traffic densities	Introduces CHQ-RA, a Q-learning-based cluster-head vehicle strategy for balanced and adaptive resource allocation.

2.7 Chapter Summary

This chapter of the thesis delivers a substantial literature study on the technology behind ITS and its supporting underlying architecture along with its applications. It discusses its exclusive attributes especially the deployment constraints in correspondence with delay-sensitive packet forwarding. The chapter explores many probable methodologies for implementing ITS applications and discusses existing strategies for addressing the shortcomings of such strategies. The recognized shortcomings initiate the proposed solutions in the thesis which aim to improve the Quality of Service (QoS) and enhance scalability, reliability, and environmental sustainability in ITS implementations. The chapter also puts together some of the significant open issues and comes up with a recapitulation of the attempts made to encounter them. The identified areas for ITS enhancement are infrastructure deployment, packet forwarding in mobile VANET environment, and prolonged travel time due to congestion and consequential environmental pollution. In the forthcoming Chapters, (3, 4, 5, 6, and 7), the thesis explores the details of the suggested findings.

3

Cost-efficient RSU Deployment and Their Energy Efficient Operating Approach for VANET

3. Cost-efficient RSU Deployment and Their Energy Efficient Operating Approach for VANET

Outline of the Chapter:

3.1 Introduction

"If we knew what it was we were doing, it would not be called research, would it?" —

Albert Einstein

Enormous enhancement of urbanization and rising the number of vehicles create unbearable traffic congestion, pollution and increase travel time, accidents that degrades environment, social life. To encounter these challenges and make transportation sector intelligent and smart 5G enabled vehicular edge computing with the incorporation of machine learning algorithms are effective paradigms that provides safe driving, traffic prediction and control [108]. Enabling these functionalities in intelligent transportation system (ITS), vehicles are equipped with plenty of sensors that collects traffic data and exchange it with infrastructures such as roadside units and backend servers. It is apparent from Chapter 2 that roadside infrastructures are requisite part of VANET that has the potential of building cooperative ITS. Roadside units handle prolific number of ITS services like traffic monitoring and forecasting, information dissemination etc. Roadside units communicate with each other and central cloud server through base stations to provide quintessential quality of services including high data speed, reliability, and low latency. Major considerations that should take into account such as the minimizing the deployment cost and optimal usage of network resources are the paramount focus of this chapter. To deploy RSUs at the critical locations for providing maximal benefits the first step should be the proper identification of most influential intersection points of a transportation network that can be used further for generating ITS applications.

Over the years, it has become a thrust area of research to manage and regulate both vehicular and pedestrian traffic in any metropolitan city, not only in developing countries like India but also in developed countries. Additionally, road safety should be the paramount concern for urban development [109, 110]. The increasing population of traffic creates immense congestion and accidents, which degrades the safety of citizens and the quality of the environment. To address the enormous challenges introduced therein, Intelligent Transport System (ITS) based models are being increasingly developed primarily using different machine-learning and deep-learning frameworks, and further supported by stochastic optimization techniques [111, 112]. Meanwhile, VANET (Vehicular Ad Hoc Network) has been utilized as an emerging solution for ITS performance enhancement by providing fast information exchange between vehicles and connected infrastructure. VANETs are dedicated to data dissemination among vehicles wirelessly in both multi-hop and single-hop manner. It ensures awareness about not only its surroundings but also comes up with plenty of applications such as commuter safety, congestion management, traffic prediction, etc. [113]. The primary challenge in dealing with VANET is its rapid movement of vehicles and ad hoc nature, which makes the network unreliable and prone to link uncertainty. Moving vehicles have less communication coverage and limited bandwidth, which degrades the quality of service (QoS) [114]. To achieve overall performance enhancement VANET needs to be assisted by roadside infrastructure. In the existing literature, parking lots, traffic lights, and various smart devices are utilized to serve VANETs. A significant portion of such ITS-based solutions is implemented in the Road Side Units (RSU) that are installed in significant traffic intersections across a region, thereby enabling Vehicle-to-everything (V2X) communication that incorporates both V2V (Vehicle to vehicle) and V2I (vehicle-to-infrastructure) communication for exchanging information between vehicles and road infrastructure [115]. RSUs are devoted to several applications for ITS including message transmission, traffic prediction, infotainment service for commuters, etc. [116]. RSUs can either be deployed in all the city junctions or else they can be deployed sparsely. The problems with the first option are manifold. Primarily, the increasing cost of equipment, installation costs, and maintenance costs shall render this option inapplicable. Secondly, the use of too many RSUs leads to synchronization issues as all RSUs must always be updated with the latest data. Finally, the increased data transfer also adds to the network overhead and further introduces security overhead as these RSUs are always vulnerable to cyber security risks. Too few RSUs, on the other hand, may result in only a partial mapping of the entire city or region. This is because of two reasons. Each RSU can only communicate and exchange information. If its fellow RSU is far away, it leads to frequent disruptions and may also result in network partition in the worst case. Secondly, the coverage area of an RSU is only limited. Unless the area of its installation is a highly influential one, the RSU-generated traffic management outcome may not be fruitful for its adjoining areas [117]. Accordingly, this paper addresses the RSU deployment issues considering the fact that in vehicular networks, fast message exchange is the fundamental challenge for any ITS service. A successful RSU placement strategy must target to connect the maximum amount of traffic with minimum message transmission delay and is the primary focus behind the proposed work in this paper. Additionally, this paper scrutinizes performance analysis of the proposed strategy in terms of coverage, packet delivery ratio, end-to-end delay and several important metrics. Briefly, RSU deployment problem thus serves as a perfect trade-off example of an optimal resource allocation problem. Given a system with S servers with R resources, the resource allocation problem aims to allocate the R resources among S servers optimally such that the overall system-level metrics in terms of server throughput and resource utilization are maximized. On a similar note, this chapter considers the traffic intersections as servers and the RSUs as resources.

However, a stark contrasting aspect is that the number of RSUs is drastically lesser in comparison to the number of junctions as discussed beforehand. Accordingly, the primary objective of this paper is to deploy the lesser number of RSUs across the entire span of a region through careful analysis and detection of the most influential regions. The secondary objective is to subsequently prove the applicability of the proposed solution by addressing a generic application of transportation problems such as traffic forecasting. Traffic prediction has a pivotal role in intelligent congestion management and vehicle mobility monitoring which enhances transportation safety. RSU can predict forthcoming traffic congestion, which will be beneficial for connected vehicles to optimize their route and speed election [118]. This paper intends to forecast larger area traffic supported by the lesser number of RSUs according to the information gathered from the connected vehicles. Literature study in chapter 2 reveals that to accomplish the aforementioned goal through prediction algorithms, extensive data analysis is required. For instance in the work cited in [119], a dataset gathered from a highway transportation system is used. The authors have categorized different traffic flows such as logistics and passengers and analyzed their similarities and differences. They have further used destination and arrival time to determine travel patterns and build a prediction framework named as Spatio-Temporal Attention-based prediction model (STAR). To alleviate commuter safety, which is the pillar of the efficient transportation system, it is additionally important to achieve robust communication between vehicle-to-vehicle (V2V) and vehicle-to infrastructure (V2I) frameworks as well. In another work [120], a novel methodology is designed on V2V performance where real data communication traces of Shanghai city are used. Both the non-line-of-sight (NLOS) and line-of-sight (LOS) link conditions are considered. The authors have investigated packet inter-reception duration for both cases and determined that LOS follows exponential distribution and the other one follows power law distribution. For reliable message broadcasting a context-aware reliable beaconing scheme is modelled where the vehicle compares link performance by two state Markov chain model. In [121], a remarkable beacon-broadcasting scheme is proposed which provides adaptive beacon control (ABC). Connected vehicles discover the environment by periodic beacon broadcasting with a fixed rate and fixed transmission power. This creates congestion and deteriorates V2V communication. To mitigate this, each vehicle follows an optimal beaconing rate for collision avoidance. A large amount of simulation-generated vehicle traces is used for performance evaluation. In a connected vehicular environment in real-time, meticulous traffic prediction is required to handle congestion and safety measures. Since data is time scaled in our case, we opt for LSTM (Long short-term memory) based prediction model [122]. Importance assessment of intersections and connected roadway links is mandatory to recognize key locations for RSU placement. Consequential points affect the functionality of complex networks more that can be identified by several parameters. Existing mechanisms in the literature that analyze the influential quotient of nodes in a network are mostly observed in social networks namely, Degree Centrality (DC), Closeness Centrality (CC), Betweenness Centrality (BC), Eigen Vector Centrality, K-shell decomposition and related such algorithms [123–124]. Application of such algorithms in transportation engineering can be found for instance in [125] where social network analysis (SNA) is used as a tool for transportation planning. Nodes are ranked according to several centrality measures. As they produce different rank lists for each centrality parameter, it is difficult to assume the ranking of the final influential nodes [126]. In general, these algorithms offer insightful results however at the cost of several trade-off parameters. For instance, DC is only concerned about the node's static structure whereas K-shell mainly considers the topological network structure of the nodes. Real-time networks such as computer networks and transportation-based networks are characterized by their dynamically varied features which may render the aforementioned algorithms insignificant in terms of influential node identification. In addition, when multiple criteria with different priority levels are used to define a single node, conventional node detection algorithms may often underperform in ranking these nodes. The proposed Intersection Influence Analysis System for Optimal RSU Deployment (IIA-ORD) framework in this chapter addresses all these issues. It implements a modified K-Shell algorithm to detect influential nodes followed by the application of a non-cooperative TOPSIS method [127] for multi-attribute-based ranking of regions in terms of their influence.

In the era of assistive and autonomous driving conventional IEEE 802.11p-based, WAVE has 10 MHz channel bandwidth restriction is not capable enough to deliver data rates in the range of 1-10 Gbps with less than 10ms of latency. This motivates us to include millimetre wave-based RSUs (mm-RSUs) in the next contribution of this chapter that has offered higher data rate and ultra-low latency in a 5G vehicular environment [128]. Deployment of RSUs and their recurring maintenance are massive costly jobs. Placing and using them intelligently is a very lucrative area of research. One of the frugal and energy efficient network resource handling strategy is to switch on them only when it is required. Urban traffic acts in a stereotypical pattern, which is quite easy to predict and take decisions according to them. Not every roadway need be attended all the time rather they can be switched on or off following the traffic conditions. This formulation is truly effective in energy saving while maintaining the QoS needs. In this work, we formulate a prediction-based RSU on-off switching model to reduce energy consumption.

3.1.1 Contributions of this chapter

The significant contributions of this chapter are therefore enlisted as follows.

- Firstly, the road network is represented in terms of nodes and edges. Transportation network analysis is done by using Static centrality metrics such as degree centrality, between centrality, and proposed derived metric cumulative traffic connection (CTC) which is based on Google's crowd-sourced traffic data. In comparison to existing datasets captured using conventional techniques, real-time crowd-sourced traffic data based work increases its applicability and scope for usage in remote areas as well as diversified traffic locations where data modelling may not always be practically feasible.

- Secondly, modification of the traditional K-shell method is another key contribution of this chapter, where the focus is on not only the topological structure but also the geographical significance of a node. This implementation compares both dynamic traffic information and static centrality measures of a node.
- Thirdly, TOPSIS is used to achieve the final list of ranked nodes using a weight allocation strategy where higher weights are considered for Traffic flow-based measurement criteria and modified weighted K-shell-based features as compared to other static centrality measures
- Implementation of the proposed II-ORD scheme is done by placing the RSUs in the designated intersections. Different performance metrics including coverage time ratio, average network coverage, packet delivery ratio, and average end-to-end delay are used for comparative performance evaluation.
- Another noteworthy contribution is the practical feasibility of the proposed scheme, which is justified using a traffic forecasting application. More specifically, traffic prediction through stacked bidirectional LSTM (SBiD-LSTM) validates the RSU deployment scheme in this chapter.
- Final novel contribution of this chapter is the implementation of an energy efficient RSU operating scheme developed for 5G-enabled mm wave based RSUs.

3.1.2 Chapter Organization

This chapter is arranged as follows. Section 3.2 introduces the proposed RSU deployment scheme with an overall view of the system model in subsection 3.2.1. This is followed by an in-depth discussion of the proposed model in subsection 3.2.2. Further subsection 3.2.3 outlines the simulation environment and establishes the performance superiority of the proposed scheme through comparative performance analysis. In subsection 3.2.4, the proof of concept is included, which performs intelligent traffic forecasting using the underlying IIA-ORD model. Next novel contribution of this chapter is illustrated in section 3.3 followed by the proposed work and performance evaluation in subsection 3.3.1 and 3.3.2 respectively. The chapter is concluded in Section 3.4.

3.2 Optimal RSU deployment using complex network analysis for traffic prediction in VANET

Road Side Units (RSUs) are an integral component of Vehicular ad hoc Networks (VANET) along with connected and autonomous vehicles. RSUs have been used to host numerous traffic sensing and control mechanisms to enhance transportation throughput in terms of safety, congestion avoidance, route planning, etc. In order to reduce installation and maintenance costs and associated network and security overhead, it is highly desirable to deploy these RSUs optimally, particularly in strategic and influential positions. While too many RSUs may increase overhead, too few RSUs may fail to map the entire region properly, resulting in erroneous computations. This paper aims to address this trade-off by incorporating a novel scheme called Intersection Influence Analysis System for Optimal RSU Deployment (IIA-ORD). The primary objective of IIA-ORD is achieved through modeling the transportation network as connected graphs and executing a modified K-shell and TOPSIS-based framework. Specifically, the network vertices are mapped with road intersections, and live traffic data is used to analyze various statistical measures, leading to the identification of influential junctions. Extensive performance analysis in an open-source simulation platform backed by real-time data justifies the performance superiority of the IIA-ORD system over existing RSU deployment strategies in terms of an overall number of deployed RSUs, average coverage, coverage time ratio, packet delivery ratio, and delay. A traffic forecasting application validates the system. The RSU is equipped with the Stacked Bidirectional Long-Term Memory (SBi-LSTM) based traffic prediction model, under which the RSU of a particular junction predicts the entire region's traffic congestion without deploying additional RSUs. Comparative analysis records high accuracy with low loss values for the proposed model in relation to the vanilla LSTM model.

3.2.1 System Model

Three fundamental algorithms drive the proposed work namely,

I. A modified weighted K-shell decomposition algorithm to analyze the influence of each node based on static centrality measures,

II. Multi-attribute based TOPSIS to rank influential nodes based on dynamic measure, and

III. Stacked bidirectional LSTM model for intelligent traffic forecasting in the RSU deployed regions to validate the proposed scheme.

To this end, the IIA-ORD model incorporates the first two algorithms and is validated using the third LSTM-based model. The overall RSU deployment model is presented in Figure 3.1. The steps are highlighted as follows.

- A road transportation network is built by selecting a real-world road network, exporting it to an open-source traffic simulator, and finally integrating different road and traffic parameters into the exported model.
- As part of the proposed II1-ORD model, different preliminary centrality parameters are computed on the designed road network. Accordingly, a modified K-shell algorithm is implemented by placing weights on different road networks based on the aforementioned parameters.
- In the next phase of the IIA-ORD model, the dynamic centrality measures are obtained using Google map APIs using crowd-sensed data. The different traffic states are analyzed as per their colour codes and accordingly, the effective traffic connection between the nodes is ascertained.
- Finally, as part of IIA-ORD, the multi-attribute-based non-cooperative TOPSIS method is applied to evaluate the influence of each node in the entire network based on which different road junctions are ranked.
- A RSU caters to communication and data transmission with vehicles for traffic management and safety. They can communicate with each other through single-hop or multi-hop networks. After optimal RSU deployment, it is therefore obvious to focus on an application that relies on RSUs. In particular, the intelligent traffic-forecasting model is designed using a stacked bidirectional long short-term memory (SBi-LSTM) model and implemented in the simulation model. The high accuracy of the executed model not only serves as an effective application of the proposed IIA-ORD scheme but also validates the proposed model as proof of concept.

3.2.2 Proposed IIA-ORD

This section provides an in-depth description of the RSU deployment procedure as per the proposed IIA-ORD model in four phases that are described as follows.

i) Phase 1: Calculation of static centrality measures

The transportation network is mapped as a graph and denoted by$G(V, E)$ where E denotes the connecting road segment of two adjacent intersections and V is the intersection. The total number of intersections is where$|V| = n$. The adjacency matrix $(AM) = \{A_{ij}\}$, $\{A_{ij}\}$ =1 if there is a connecting road exists between intersection i and j. It has further been considered that the communication range for each RSU is the same and whenever vehicles come to its coverage range, it will receive its services. For the deployment purpose, several centrality measures are considered and determined for the transportation network. These are discussed in the following.

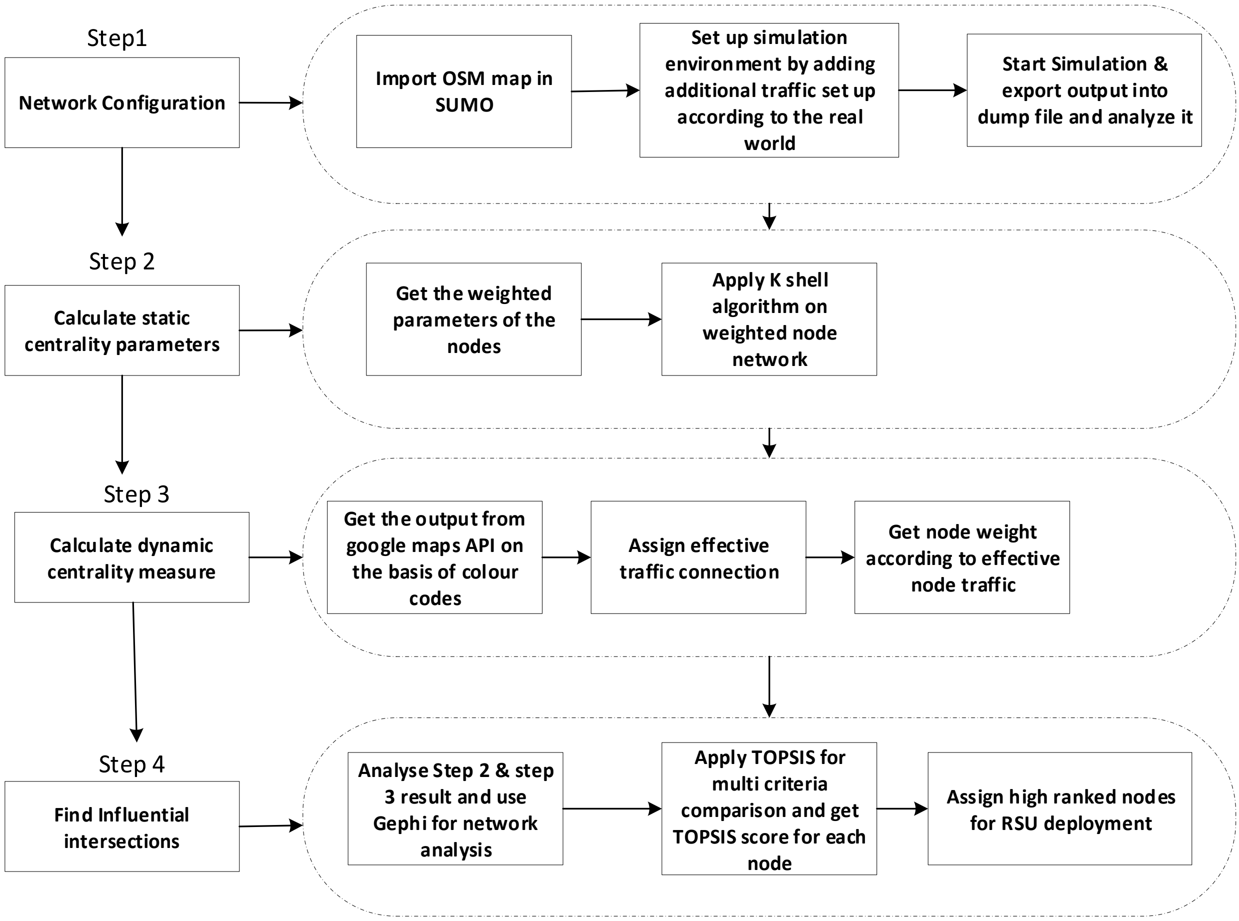


Figure 3.1: Flow chart of Operation

1. *Degree Centrality (DC)* defines significance of a node by comparing its connected neighbors. Higher the degree means higher the influence. DC is defined by

$$DegC(i) = \sum_{j}^{n}\{A_{ij}\} = Deg_i \tag{3.1}$$

   Here, Deg_i is the degree of the node i.

2. The second important metric is *Betweenness Centrality (BC)*, which counts the number of shortest paths through a particular node. It is given by,

$$BTC(i) = \sum_{j,k \neq i}^{n} \frac{SP_{jk}(i)}{SP_{jk}} \tag{3.2}$$

where SP_{jk} is the number of shortest path from $j\ to\ k$ and $SP_{jk}(i)$ is the number of shortest path through node i. It is obvious that in any network, node importance is higher if more number of shortest paths is passing through it.

3. *Eigenvector Centrality (EVC)* defines the criticality of a node by not only the number of its connected links but also by the influence of them. EVC is formulated as,

$$\mathrm{EVC(i)} = \frac{1}{\mu}\sum_{j=1}^{n}(A_{ij}x_j) \tag{3.3}$$

μ is the largest Eigen value of adjacency matrix (AM) and x_j is the value of jth entry of the Eigen vector related to μ.

ii) Phase 2 : Modified weighted K-shell based Traffic Junction detection

In *K-shell Decomposition Method,* each node of the network is allocated with an index, which is called k-shell index. Firstly the indexing starts with the deduction of the nodes having degree D =1 from the network. Their K shell index will be $K_n = 1$. Then the nodes with degree D>1 is clipped according to their k shell index value. This process continues until all the existing nodes are covered. A higher K-shell index value denotes core nodes of the network, while lower values symbolize peripheral nodes. K-shell index value is thus used to understand the topological position of a node in a network and is considered for detecting influential traffic junctions in the developed transportation network [129]. Classical K-shell decomposition only considers a node's degree. On the contrary, this paper considers not only the topological but also the geographical importance of a node. This is because, in a transportation network, a node's importance in traffic is greatly influenced by its nearby point of interest (POIs). In Several POIs like hospitals, banks, schools, universities, police stations, and shopping malls are responsible for determining the influence of the corresponding traffic intersection. Accordingly, the conventional K-shell decomposition algorithm is modified by including weights in the node. The process is illustrated in algorithm 3.1. Specifically, when an intersection has more than one POIs within its RSU range, then it will be assigned more weight. Whenever a POI's location is nearby from two different nodes, only the shortest distance node is considered for weight calculation.

Weighted degree of a node is therefore given by,

$$k^w = \alpha K_n * \left[\frac{\sum_{i=1}^{N} w_{ij}}{N}\right] \quad \text{Where,} \quad w_{ij} = \gamma \sum_{x=1}^{m} POI,\ (x = 0,1,\dots n) \tag{3.4}$$

Where K_n is the k-shell value of a node and α is tunable parameter. $\sum_{i=1}^{N} w_{ij}$ is summation of its connected link weights. N is the number of connected links of the node. Link weight is assigned by its allocated POIs. Moreover, γ is the scaling factor and m is the number of POIs denoted by I_x.

Algorithm 3.1: Weighted K-Shell Decomposition

Input: Transportation Network G (V, E)
Parameter: Weighted Degree k^w
Output: Queue $[v, k_w]$ where,$v \in V$ and k_w is weighted k-shell value of vertex v
Initially vertices assigned with default k-shell value $k^w = 1$
While ! $is\ Empty(V)\ do$
    Repeat
        Calculate weighted degree of all intersections as per Equation
        Search all intersections in G with weighted degree $\leq k^w$
        For each such node v with weighted degree k^wdo
            Set k_w=k^w
            Restore k_w in rank queue
            Clip node v from G
        Upgrade k^w to further increment until all vertices have weighted degree >k^w

iii) Phase 3: Determination of Derived Metrics based on Crowdsourced data

In the third phase, derived metrics such as effective traffic connection and total cumulative traffic connection are proposed and determined to capture the overall dynamics of the road transportation network. In this regard, data from the Google Maps traffic database is used for analysis. The motivation behind using Google Maps is drawn by two factors. Firstly, lack of any credible open-source database for road traffic statistics with respect to Indian cities is a major hindrance to advanced data-centric research in the ITS domain. Secondly as a cost-effective and viable alternative, Google Maps are efficient and feasible way to collect real-time traffic data.

Google provides live as well as historical crowd-sourced traffic data through different colour codes. For instance, Green code indicates negligible traffic delay; orange code denotes comparatively higher traffic whereas red and dark red colour codes signify varying levels of congested road conditions [130]. In addition, Google maps provide traffic data in two forms, namely i) historical data which is the average travel duration at a time for a given road length and ii) real time live traffic data that keeps on varying based on prevalent traffic situations.

Accordingly, these data maps for the areas under study are downloaded and stored in a computer after every fixed time interval as digital images.

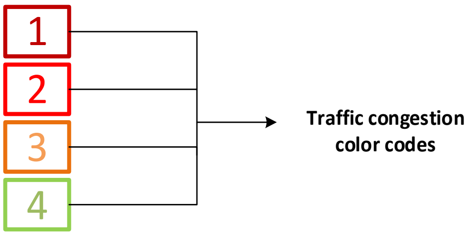


Figure 3.2: Google traffic colour codes and corresponding assigned values

For each traffic condition, a congestion colour code is allocated which is then transformed into numerical values as shown in the above Figure 3.2. The colour represents the traffic condition as shown in the google maps while the mapped numerical values are provided adjacently. Accordingly, a derived metric namely, the effective traffic connection (ETC) is proposed that determines the traffic conditions between two nodes based on these congestion codes transformed values as well as the node degree values. Mathematically, the ETC is given by,

$$ETC(i,j) = \frac{Deg_i \times Deg_j}{{TCC_{(j|i)}}^2} \tag{3.5}$$

Where Deg_i and Deg_j are degree of node i and j respectively, $TCC_{(j|i)}$is the Traffic Color Code between node i and node j.

Working Example: A snapshot of the Google Map with crowdsourced traffic data is illustrated in Figure 3.3. The aim is to obtain ETC between junctions A and B as highlighted in the figure. Based on the aforementioned procedure, it s found that TCC (B|A) is 3 as given by the colour code mapping. It must be noted that TCC (B|A) and TCC (A|B) are different and the same can be easily obtained from Google data because it measures traffic congestion across every road direction.

Figure 3.3: Traffic Colour code Instance

Subsequently, the traffic connection of each node is received by the cumulative sum of its effective traffic connection with other connected nodes in the network and is given by,

$$TC_{(i)} = \sum_{j=1, j\neq i}^{k} \frac{Deg_i \times Deg_j}{TCC_{(j|i)}^{\ 2}} \tag{3.6}$$

Where k are the number of nodes that are connected with node i.

This leads to another proposed derived metric namely, the total cumulative traffic connection (CTC) of a particular node which can be defined as the summation of its traffic connection with respect to time. It can be expressed as follows.

$$CTC_{(i)} = \sum_{t=0}^{r} \sum_{j=1, j\neq i}^{k} TC_{(i)} \tag{3.7}$$

iv) Phase 4 : RSU deployment using ranked Traffic Junctions

Finally, each node is characterized using three types of metrics including the centrality measures, the K-shell index value and the proposed derived measures. The final objective is to rank these nodes in order to select only the top ranked influential nodes for RSU deployment. This problem is mapped as a multi-attribute decision making model (MADM) where attributes are the different node measures while decision is to rank the nodes. The same is solved by selecting the TOPSIS (**Technique for Order of Preference by Similarity to Ideal Solution)** [130] model.

TOPSIS is a way to assign the ranks on basis of the weights and the impact of the given factors. Weight signifies how much a given factor contributes to the overall ranking procedure. In the real-time road transportation networks, time-varying parameters such as effective traffic connection should be given higher weights compared to the static centrality based measures. Accordingly, the proposed algorithm is described as Algorithm 3.2.

Algorithm 3.2: Traffic Junction Ranking using TOPSIS

Input: $G(V, E)$ the network,q number of criteria that includes BC, EC, Weighted K-Shell, ETC; ω weight for the criteria

Output: Sorted Influential Road Junctions $[Imp]$

1. Organize the Evaluation matrix with number of nodes n as alternatives and q centrality parameters as criteria.

$$E = \begin{bmatrix} E_{11} & . & E_{1q} \\ . & . & . \\ E_{n1} & . & E_{nq} \end{bmatrix}$$

Where $n = |V|$ is the number of Nodes, here intersections,$e_{ij} = C_j(i)$ $(i = 1,2, \ldots, n; j = 1,2, .. q)$

2. Calculate normalized column of E and assign weight as $M_{ij} = \frac{e_{ij}}{\sqrt{\sum_{k=1}^{r} e_{kj}{}^2}} .\omega_j (i = 1,2, \dots n; j = 1,2, .. q)$ to create Attribute matrix $T = \begin{bmatrix} T_{11} & . & T_{1q} \\ . & . & . \\ T_{n1} & . & T_{nq} \end{bmatrix}$
3. Calculate positive P_j^{+ve} and negative N_j^{-ve} ideal solutions for attributes j; $P_j^{+ve} \begin{cases} \max\{M_{ij} | i = 1,2, \dots n\}, & j =\in T_p \\ \min\{M_{ij} | i = 1,2, \dots n\}, & j =\in T_c \end{cases}$ &
$P_j^{-ve} \begin{cases} \min\{M_{ij} | i = 1,2, \dots n\}, & j =\in T_p \\ \max\{M_{ij} | i = 1,2, \dots n\}, & j =\in T_c \end{cases}$
Where T_p & T_c are profit and cost attribute respectively.
4. Distance for each alternative i to its positive ideal solution and negative ideal solution
$$Dis_i^{+ve} = \sqrt{\sum_{j=1}^{q} (m_{ij} - P_j^{+ve})^2}, Dis_i^{-ve} = \sqrt{\sum_{j=1}^{q} (m_{ij} - P_j^{-ve})^2}.$$
5. Node importance is more if its value is closer to the positive ideal solution and farther from the negative ideal solution. The Topsis score which indicates relative closeness to the ideal solution is $Topsis_i = {Dis_i^{-ve}} \big/ {Dis_i^{+ve} + Dis_i^{-ve}}$
6. Important nodes are denoted as $Imp = [\, Topsis_1, \, Topsis_2, \dots, Topsis_n]$.
7. Imp vector is ranked according to descending order based on each criterion of each node.
Sort [Imp] = sort ([$Topsis_1$, $Topsis_2$, ... $Topsis_i$, .., $Topsis_n$]) = [$Imp^1, Imp^2, \dots, Imp^n$]

Based on the outcome of the *Imp* list, the top ranked nodes are selected and inserted into the *Imp* list by considering a threshold metric that differentiates between higher and lesser influential nodes. This paves the way for RSU deployment across only the influential nodes in the *Imp* list.

3.2.3 Performance evaluation of Proposed IIA-ORD Model

This section evaluates the performance of the proposed IIA-ORD model by taking Kolkata as the sample city. Kolkata being one of the major metropolitan cities of India and gateway to the north-eastern India is selected for this analysis because the city is characterized by a complex maze of roads and sub-lanes, wide modes of transport and high vehicular density. All the factors necessitate the RSU deployment for formulation of smooth and dynamic traffic regulation and safety policies.

More specifically, the evaluation is based on different case studies by selecting prominent regions in the city. Data for the case studies has been received from google maps based on the colour-coding scheme as already discussed. It may be noted that the grey colour in the map indicates that there are not enough readings in the passing vehicles (google support, 2019). The following open-source platforms are used for the model design and simulation.

- Gephi [131], an open-source complex network analysis and visualization tool written in Java on the NetBeans platform is utilized for centrality calculations and network diagram creation. In diagram node size is represented according to their influence strength.
- SUMO is a microscopic, open source traffic simulator in which each vehicles behaviour can be monitored and controlled [132] and furthermore, it allows the backend coding of different network nodes for traffic regulation policies.
- Open Street Map [133] facilitates in evaluating real-world maps by allowing us to import the different case-study based regions from Kolkata into SUMO for simulation.
- NS2 has provided the entire necessary infrastructure to initiate the communication and networking operations with respect to the vehicles and the RSUs.

For each case study, the intersections within the network are identified as nodes and roads are treated as edges. Weight is assigned according to the centrality parameters and traffic volume and intersection popularity is considered. In general, for any dense urban city, it is a very common scenario where two important nodes are very closely located. These set of nodes are represented as a single node in this paper as one single RSU can cover both the nodes. To this end, the threshold distance is considered as 200m. It signifies that if the distance between two nodes is below this range then they will be treated as a single node. This greatly reduces system redundancy and complexity. In SUMO, a particular area can be imported from Open Street Map or it can be generated manually. In our case we have imported our case studies from OSM map. Here, edge includes the number of lanes as per roadway. Traffic lights follows the default cycle of 120 seconds. SUMO further provides the point of interests (POIs) which is necessary to apply node weights. The information about the POIs is taken from OSM. Initially the command *netConvert* is used to process the *.xml* file that contains all the *IDs* to segregate two directions of the roadway. To begin the simulation, it is necessary to implement that xml configuration file with .config extension. Vehicle trip data is subsequently generated by SUMO's *randomTrips.py* tool. Floating Car Data (FCD) is saved for all time steps in .xml format. This FCD data is then converted into flat file (.csv) format. *CSV* files contain number of vehicles in particular edges, vehicular speed, total vehicular count, and average vehicular speed at each time step. The underlying network and the communication modes are simulated by using open source network simulator NS2 following the 802.11p standard. Figure 3.4 illustrates the proposed simulation setup.

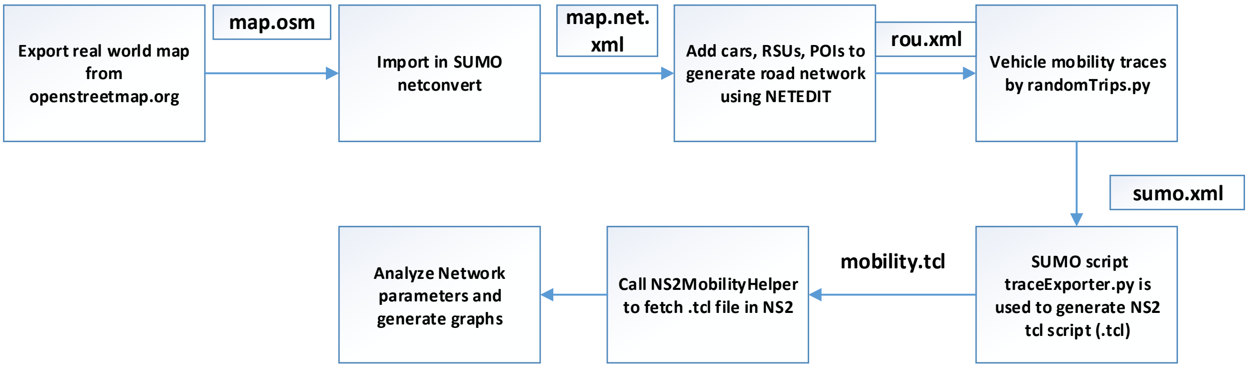


Figure 3.4: Simulation Setup for evaluating the proposed IIA-ORD framework

Based on the simulation platform, two case studies are considered by selecting the Jadavpur region and the Shyambazar region from the southern and northern parts of the city respectively (Figure 3.5 and 3.6). The basis for their selection is primarily attributed to their significance in terms of high vehicular density and places of interest as well as their topological significance in terms of their increased coverage and connectivity to surrounding regions. As per the proposed algorithm, the derived metrics along with the network topological properties are depicted for each case study in Table 3.1. First case study contains 1505 nodes and 3683 edges. The corresponding network properties as implemented in NS2 are summarized in Table 3.2. Accordingly, the portions are extracted from the OSM and imported in SUMO. The same is illustrated in Figure 3.5 and Figure 3.6 respectively. Average betweenness is assigned to estimate the average frequency of shortest path passing through a node.

Table 3.1. Network Topological Properties

Parameter	**First Case Study**	**Second Case Study**
No. of Nodes	1505	1016
No. of Edges	3683	2493
Maximum Degree	4	5
Minimum Degree	1	2
Average Degree	2	2.15
Average Betweenness	410	465.11
Area	$4\ km \times 4\ km$	$4.5\ km \times 3\ km$

The proposed IIA-ORD methodology is applied in both these regions. The static centrality measures including the BC, the EVC parameters for both the regions are tabulated, and subsequently, the modified weighted K-shell based Traffic Junction detection is performed by assigning K-shell values to all nodes. The corresponding transportation network as visualized in Gephi is illustrated in Figure 3.7(a) and Figure 3.7(b) respectively. A node with higher weight is visualized with a bigger circle highlighting its significant influence over other regions.

Table 3.2. Network Data Traffic Properties

Parameters	**Values**
Mac	IEEE 802.11p
Data rate	2 Mbps
Message Size	256 bytes
Transmission Range V2V	250 m
Carrier Frequency	5.9 GHz
Channel Bandwidth	10 MHz
Radio propagation model	Two way ground

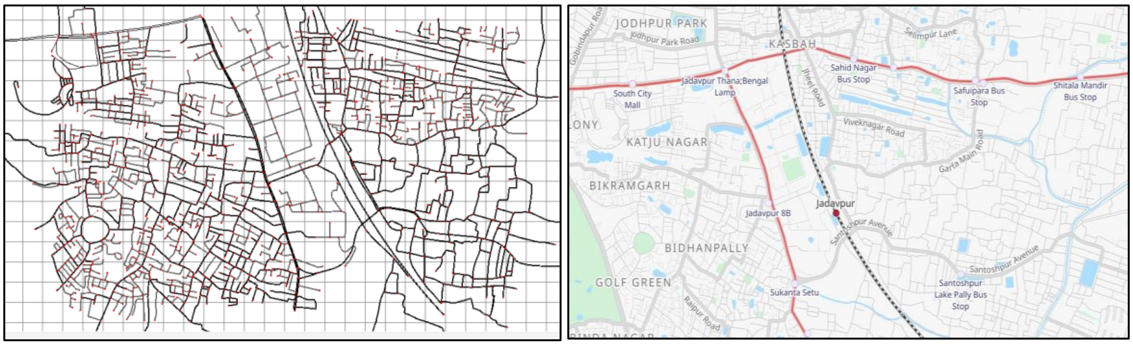


Figure 3.5 Jadavpur Area Transportation Network Map - First Case Study

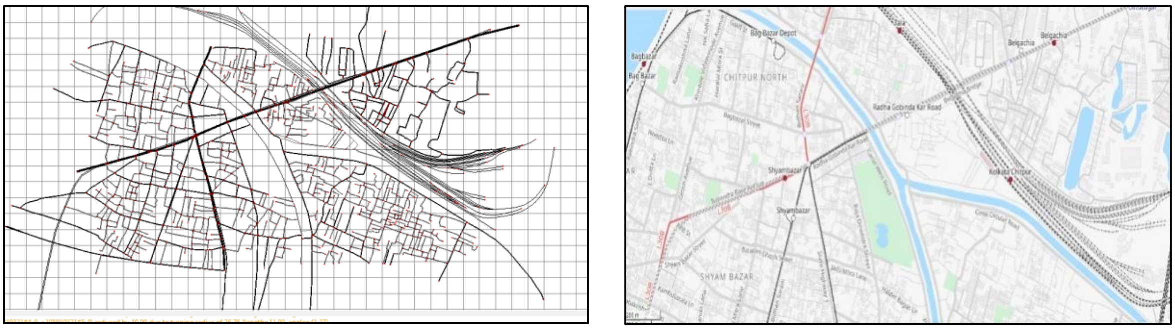
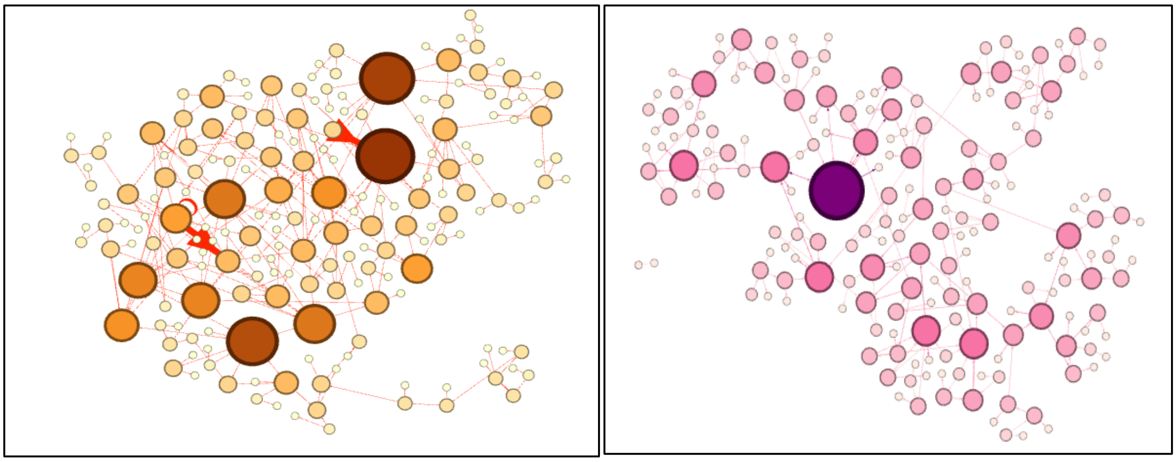


Figure 3.6 Shyambazar Area Transportation Network Map – Second Case Study

The Effective Traffic Connection metric is derived for both regions and finally, the most influential nodes in each region are selected by ranking them as per the proposed algorithm. Table 3.3 and 3.4 respectively highlight the ranked nodes of each case study. Thus if a threshold is selected, all the nodes ranked higher than the threshold become eligible candidates for RSU deployment. This reduces the number of RSUs which otherwise need to be deployed in every node for V2X communication and traffic management operations. In order to justify this statement and further compare with existing works in this domain, the following section considers different performance metrics as discussed below.



(a) (b)

Figure 3.7: Transportation network structure is visualized in Gephi (ver. 0.8.2) (a) Jadavpur Area- First Case Study (b) Shyambazar Area- Second Case Study

Table 3.3: Top 12 Influential nodes for first case study according to evaluated parameters

	Weighted K shell Value		Effective Traffic Connection		Betweenness Centrality		Eigen Vector Centrality			
Rank	Value	Node	Value	Node	Value	Node	Value	Node	**Topsis Score**	**Node**
1	30	5	25.17	5	805	18	0.63	35	0.62	5
2	25	25	24.65	25	769	97	0.58	25	0.60	25
3	20	18	18.96	35	698	5	0.42	18	0.56	35
4	16	35	18.57	18	665	35	0.41	97	0.47	18
5	15	41	17.83	80	585	25	0.39	5	0.43	80
6	14	80	15.89	97	578	108	0.38	108	0.38	97
7	13	97	15.16	41	482	67	0.36	97	0.35	41
8	12	108	14.3	108	465	80	0.34	80	0.36	67
9	12	67	14.85	78	455	78	0.30	127	0.419	108
10	10	8	12.25	67	438	127	0.30	78	0.349	8
11	10	78	12.0	8	434	8	0.25	8	0.372	78
12	9	127	10.70	127	420	67	0.23	67	0.370	127

To evaluate the efficacy of the proposed IIA-ORD scheme, several performance metrics have been used as discussed in the following.

1. *Coverage ratio* –It is defined by the ratio of the number of intersections deployed with RSUs to the total number of intersections in the network.

2. *Coverage time ratio* – It is defined by the ratio of a vehicle-spent time in the RSU coverage range to the total time spent by the vehicle during the whole road network movement. A higher value indicates that RSU can provide long-term service to the vehicle.
3. *Contacts per trip* – It refers to the average number of communication pings among the vehicles and the RSUs throughout one trip. The higher the number, the higher is the QoS performance.
4. *Packet delivery ratio* – It denotes the ratio of the number of data packets received by the RSU to the number of data packets transmitted from the source vehicle.
5. *Average end-to-end delay* – This metric signifies the time required by a data packet to be transmitted from the source node to the destination node.
6. *Number of RSUs* – This is one of the core objectives of this paper where the number of deployed RSUs is compared for each scheme for varying transmission ranges with respect to the different case studies.

Table 3.4: Top 12 Influential nodes for second case study according to evaluated parameters

	Weighted K shell Value		Effective Traffic Connection		Betweenness Centrality		Eigen Vector Centraility			
Rank	Value	Node	Value	Node	Value	Node	Value	Node	**Topsis Score**	**Node**
1	30	8	26.98	8	785	8	0.94	8	0.64	8
2	22	200	22.80	45	705	200	0.66	68	0.63	45
3	20	45	20.24	200	670	68	0.63	200	0.61	200
4	18	68	18.86	68	632	45	0.56	45	0.49	68
5	16	15	16.66	15	580	15	0.48	230	0.46	15
6	16	230	15.38	107	570	230	0.39	15	0.33	230
7	12	140	14.32	230	492	250	0.35	140	0.26	140
8	12	107	14.20	140	455	107	0.28	250	0.248	107
9	10	250	12.88	250	435	140	0.25	235	0.241	250
10	9	235	12.26	235	405	120	0.23	107	0.229	235
11	8	151	12.0	120	388	235	0.20	151	0.209	151
12	8	120	10.86	151	370	151	0.20	120	0.202	120

The proposed IIA-ORD model is compared with respect to these indicators against related works in literature as further highlighted in the following.

- CDA DC [32]: This scheme proposes RSU deployment based on degree centrality measures.

- CDA CC [32]: This scheme determines RSU deployment considering centrality measures.
- IHDA [42]: In this framework, the node popularity of a particular node is considered for RSU deployment.
- Random: Finally, as the baseline model, a random placement scheme is considered. This scenario does not impose any node influence category and randomly places RSUs based on demand and applicability

Firstly, in terms of coverage ratio depicted in Figure 3.8, it is observed that IIA-ORD gives good coverage when transmission range increases from 150m to 550m. Its overall percentage of improvements are 27% and 11% when compares with CDA-DC and IHDA respectively. On the other hand, the coverage time ratio depicted in Figure 3.9 of IIA-ORD is 63% and 37% more than CDA-DC and IHDA respectively. The improved performance of the proposed algorithm can be primarily attributed to the fact that the IIA-ORD considers not only the graph features through the weighted K-shell algorithm but also considers both the centrality measures (degree centrality, eigen vector centrality) as well as the derived metrics (effective traffic connection).

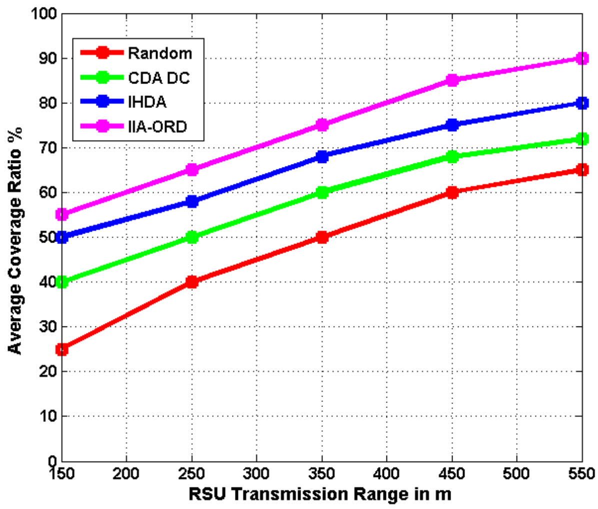


Figure 3.8: Comparison of Average Coverage Ratio with respect to different RSU Transmission Range

Improved coverage ratios also mean that IIA-ORD requires significantly lesser number of RSUs to be deployed in comparison to other schemes and the same is verified in Figure 3.10. An interesting observation is that IHDA has scored above both DC and CC based algorithms on all the three metrics. This is because IHDA also partially considers other factors such as vehicle contact time, intersection connectivity, and intersection coverage capacity during RSU deployment. However, it underperforms with respect to IIA-ORD primarily on two factors as stated in the following.

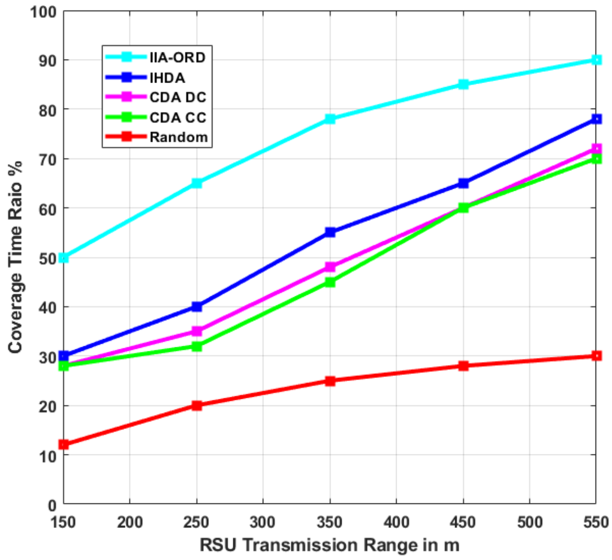


Figure 3.9: Comparison of Coverage Time Ratio with respect to different RSU Transmission Range

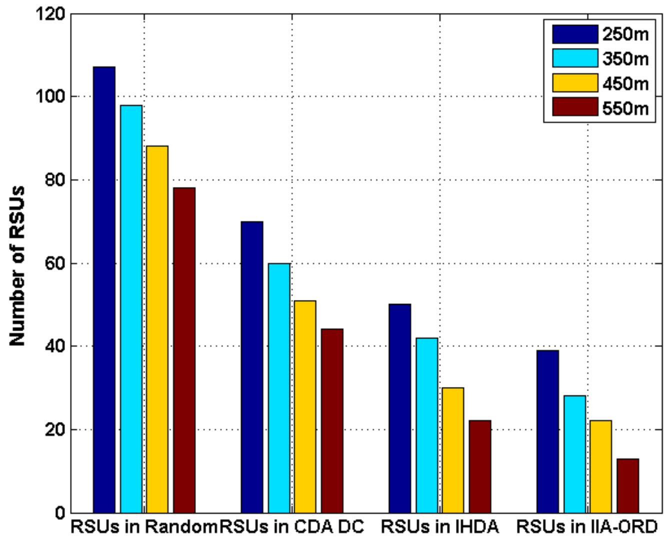


Figure 3.10: Comparison of Number of RSUs based on Increasing Transmission Range

1. Modified K-Shell decomposition helps in not only identifying the most influential regions but also tags each region with a "influence spreading metric". This indicates how much each region can affect the surrounding regions. This metric plays a key role in ranking the different places based on their influence in TOPSIS phase of IIA-ORD scheme.

2. Variation of weights in both K-shell as well as in the TOPSIS methods allow the dynamic tuning of how each parameter individually affects each specific region.

However, since both IHDA and IIA-ORD consider vehicular attributes for each region, their contacts per trip metric are more or less comparable to each other, this is depicted in Figure 3.11. IIA-ORD still marginally scores above IHDA which can further be attributed to two factors namely – 1) ranking of regions in IIA-ORD that ensures that no higher-ranked intersections are devoid of RSUs even if they are near to each other, as these regions witness maximum vehicular density; 2) selection of the threshold parameter in TOPSIS that further makes sure that the less influential RSUs are left out from RSU deployment, thereby increasing the average contacts per trip with respect to all RSUs.

Finally, the QoS metrics in terms of packet delivery ratio (PDR) and end-to end delay are studied using NS-2 in Figure 3.12 and 3.13 respectively. Overall improvement of PDR of proposed IIA-ORD is 12% and 40% in comparison with IHDA and CDA-DC respectively. On the other hand, the average end-to end delay decreases 32% and 53% for IIA-ORD when compared with IHDA and CDA-DC respectively.

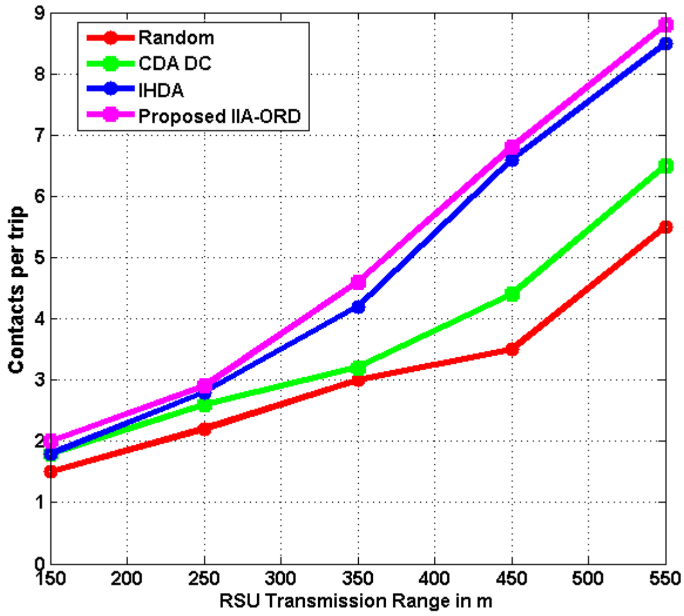


Figure 3.11: Contacts per trip on Increasing Transmission Range

An interesting observation is the random scheme, which records lower end-to-end delays compared to advanced schemes such as IHDA, CDC-DC and CDC-CC. This is partly because this random scheme may succeed in one simulation run and fail in another run. Secondly, random placements do not take into account RSU counts. Hence, it is quite imperative that more the number of RSUs, lesser will be the end-to-end delays.

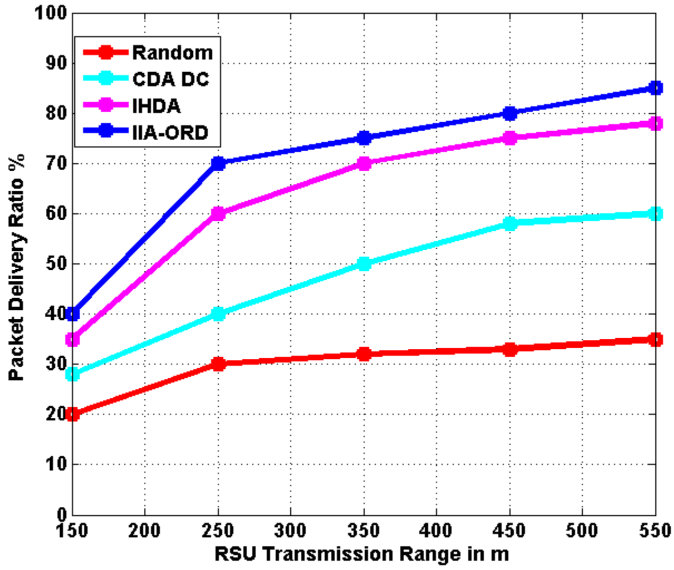


Figure 3.12: Packet Delivery Ratio with respect to different RSU Transmission Range

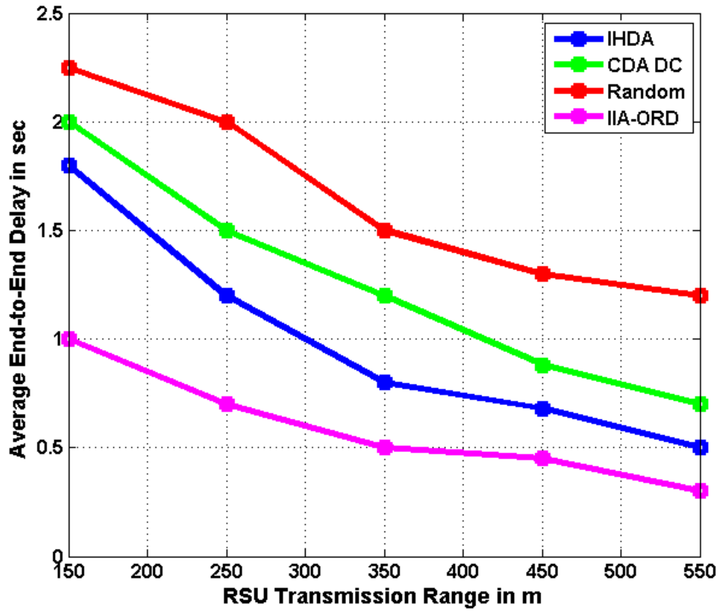


Figure 3.13: Average End-to end delay with respect to different RSU Transmission Range

3.2.4 Proof of Concept

In addition to the performance superiority of the proposed IIA-ORD scheme over related works, a significant contribution of this paper is the application of the scheme for intelligent traffic forecasting operation. This not only serves as proof of concept but also provides a platform for researchers to experiment novel traffic safety and management policies under the deployed RSU scheme. The proposed framework is described first followed by the analysis and comparative evaluation.

A. Stacked bi-directional LSTM architecture

Accurate traffic forecasting is necessary for transportation management and is considered as an application to be evaluated under the proposed IIA-ORD based RSU deployment model. To this end, stacked bidirectional long short term memory (LSTM) architecture is selected as it deals with sequential data [134], [135]. LSTM is unique because of its spontaneous ability to grasp long-term sequence data [108]. In Figure 3.14, the standard structure of a LSTM cell is depicted. A memory unit named as cell is incorporated into the network that deals with long term data. Cell unit is made up with input gate, forget gate and output gate. Forget gate accounts for the long-term memory h_{t-1} (previous cell output) and the input datax_t. This is expressed by the following formula

$$f_g^t = \sigma(w_f.[h_{t-1}, x_t] + b_f) \tag{3.8}$$

$w_f$denotes the weighted metrics, b_f is the bias vector and σ is sigmoid function. Memory gate aims to define what new information is reserved in a cell state. Memory gate has two components one is the sigmoid part that discovers the values that are required to be updated; and another one is $\tan h$ part. Second part produces a new candidate value vector that becomes candidate memory. This method is expressed in following equations. Here, w_i and b_i is the weight metrics and bias vector respectively.

$$i_g^t = \sigma(w_i.[h_{t-1}, x_t] + b_i) \tag{3.9}$$

$$\widetilde{C_t} = \tan h\,(w_C.[h_{t-1}, x_t] + b_C) \tag{3.10}$$

In this point previous cell state C_{t-1} is changed to achieve the value of C_t.

$$C_t = f_g^t * C_{t-1} + i_g^t * \widetilde{C_t} \tag{3.11}$$

At the end, the output of LSTM is decided by the state of the cell. Sigmoid function determines which part of the cell state will be the output and further it goes through the $\tan h$ layer. Two of them are multiplied to achieve the final output.

$$o_g^t = \sigma(w_o.[h_{t-1}, x_t] + b_o) \tag{3.12}$$

$$h_t = o_g^t * \tan h\,(C_t) \tag{3.13}$$

Although one single LSTM unit is capable to predict traffic congestion, this paper opts for enhanced version in the form of stacked bidirectional LSTM [123] for enhanced accuracy. In this model, more than one LSTM unit is gathered together where output of non-last layers act as input to the following layer. Two layers process the input data sequence. One layer operates in forward direction and another one chooses the backward direction to capture both forward and backward dependencies of traffic data. Diagrammatic representation of Stacked Bidirectional LSTM is depicted in Figure 3.15.

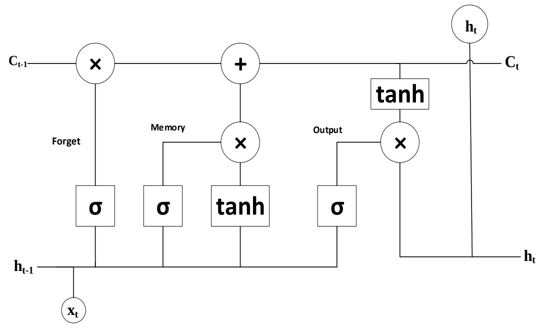


Figure 3.14: LSTM Architecture

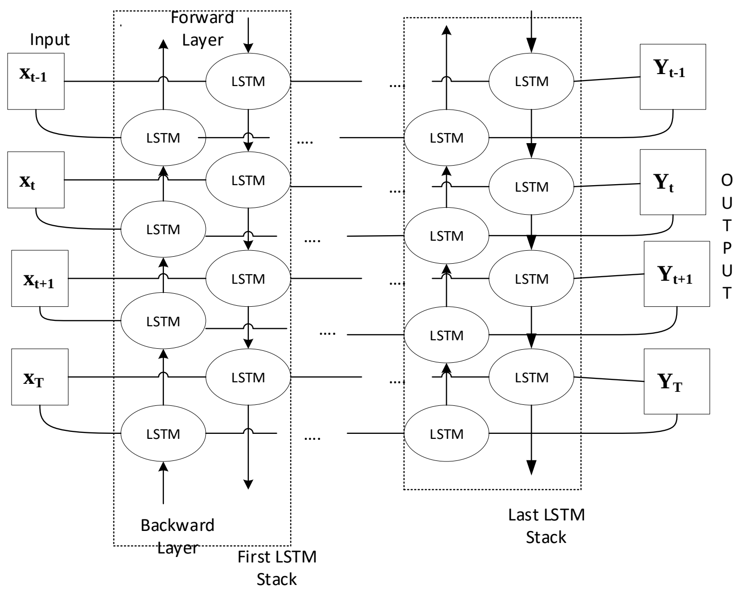


Figure 3.15: Stacked Bidirectional LSTM

B. Proposed Traffic Forecasting application

Traffic volume is taken in 10 time points in 24 hours of target road segment. The data is measured for several days. Traffic count average of single intersection in one hour is treated as input. Input vector contains 10 values for each time points. Specifically, the google traffic data is observed for the period from 01/12/2021 to 31/12/2021. Stacked bidirectional LSTM as discussed above is used with Python based on Keras module for machine learning with TensorFlow in the backend. Input data is categorized in two parts – one is training and other one is testing. First 70% of the data is allotted for training and the remaining 30% is allotted for testing. Figure 3.16 shows sample heat map of one-week traffic. Darker colour denotes congested traffic. Required parameters to implement SBi-LSTM are listed in table 3.5.

Table 3.5. Parameters to implement SBi-LSTM

Parameter	**Value**
Model type	Sequential
No. of time steps	10
No. of dense layers	1
No. of neurons	50
Activation Function	Sigmoid
Optimizer	Adam
Epochs	200
Merge mode	Sum

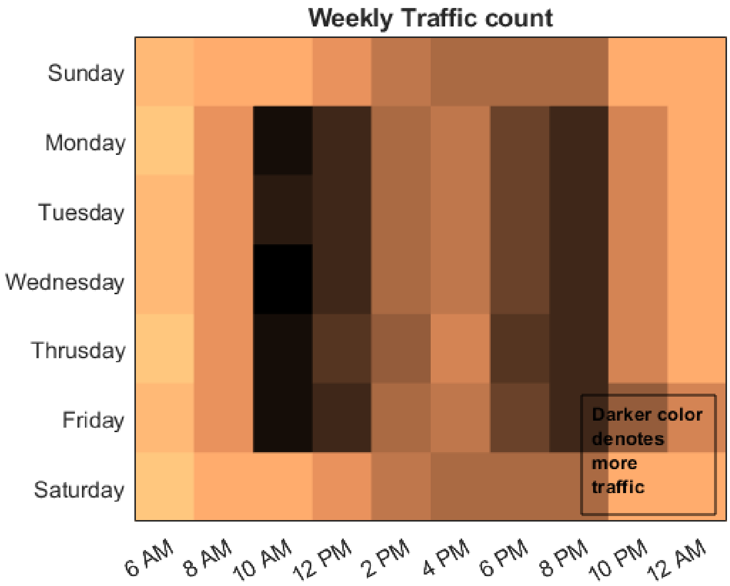
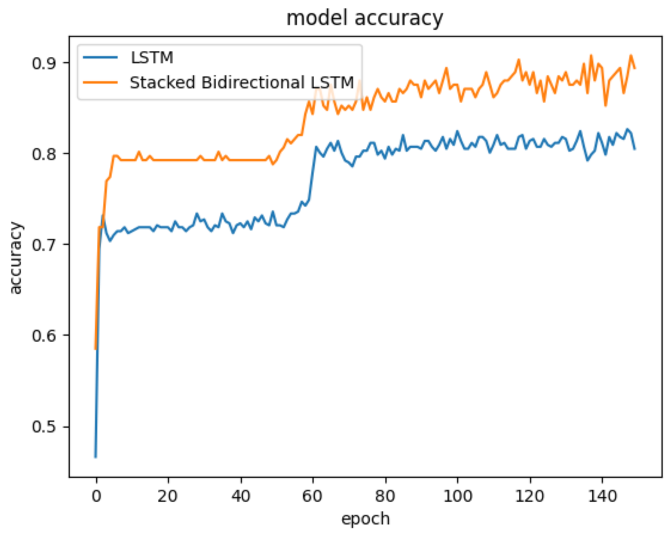


Figure 3.16: Sample heat map of collected traffic data

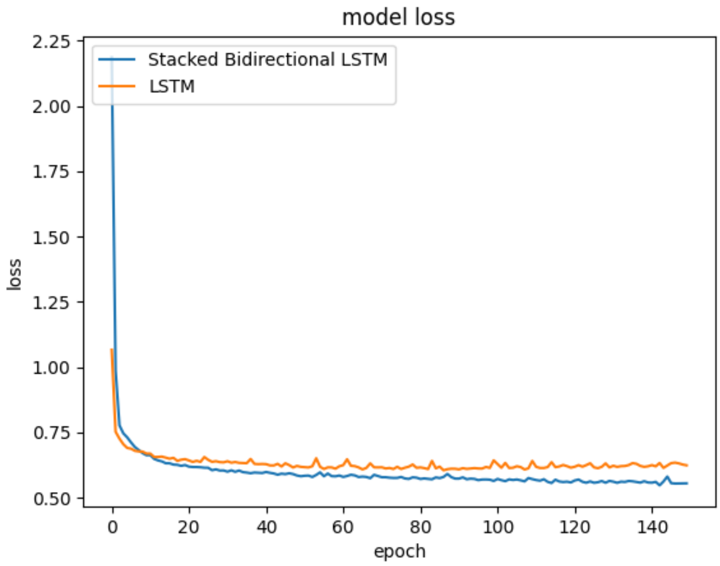
The traffic forecasting application is compared in terms of accuracy for both SB-LSTM and standard LSTM. SB-LSTM outperforms LSTM in terms of accuracy percentage, which is a measure of closeness to the actual value. It can achieve maximum of 86% accuracy for the predicted traffic compared to 80% for LSTM. Figure 3.17 (b) describes the loss performance over epochs for both standard LSTM and stacked bidirectional LSTM. The metric used is Means square error (MSE) that is calculated by the average of the squared differences between the predicted data and actual data. Finally, Figure 3.17 (c) depicts the comparison with respect to the number of layers to be used in Stacked Bidirectional LSTM keeping in mind both accuracy percentage and computation time in second. As three-layered model shows balanced performance for both accuracy percentage and computation time, the same is used in this paper.

C. Implementing the proposed application in IIA-ORD Model

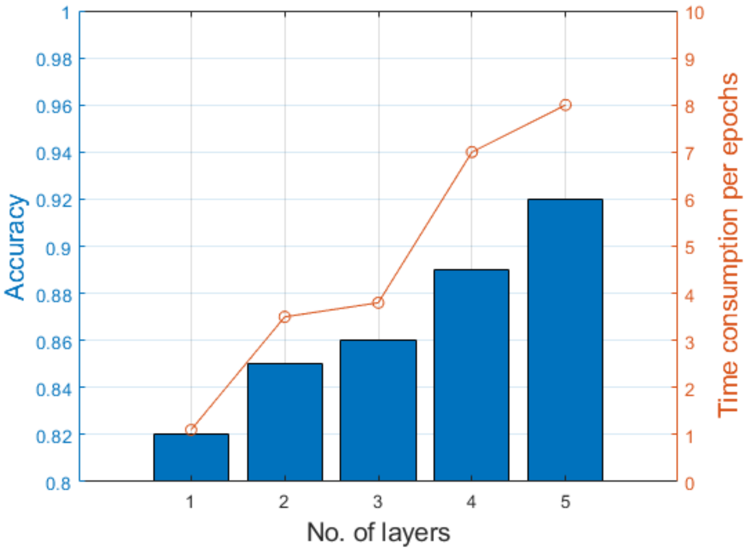
As proof of concept, the designed traffic forecasting application is tested under the IIA-ORD scheme by considering a vanilla scheme where RSUs are deployed in all intersections. The basis for evaluation is to evaluate whether the reduced number of RSUs in IIA-ORD scheme can succeed in forecasting traffic congestion with almost similar accuracy levels as the vanilla scheme.



(a)



(b)



(c)

Figure 3.17: (a) Accuracy analysis for LSTM AND SB-LSTM (b) Loss analysis for LSTM AND SB-LSTM (c) Comparison of Sb-LSTM layers for both accuracy and computation time

Accordingly, two scenarios are created in the IIA-ORD model that include – 1) the influential area under the direct coverage of the RSUs; 2) extended or larger traffic prediction area where RSUs are directly not deployed. This is depicted in Figure 3.18.

Comparisons are drawn for a single RSU placed only at the influential region versus multiple RSUs placed at all locations and the same is illustrated in Figure 3.19(a) and Figure 3.19 (b) respectively. It is observed that even with a single RSU as per the IIA-ORD scheme, it is possible to predict the traffic congestion of extended places with sufficient accuracy. It is quite obvious that the vanilla scheme based evaluation in Figure 3.19 (a) witnesses higher accuracy levels. However, IIA-ORD scheme achieves the trade-off between reduced number of RSUs and increased accuracy levels more efficiently as compared to the vanilla scheme.

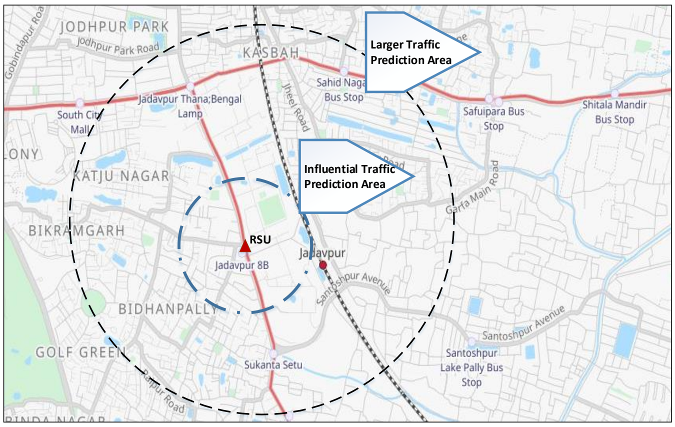
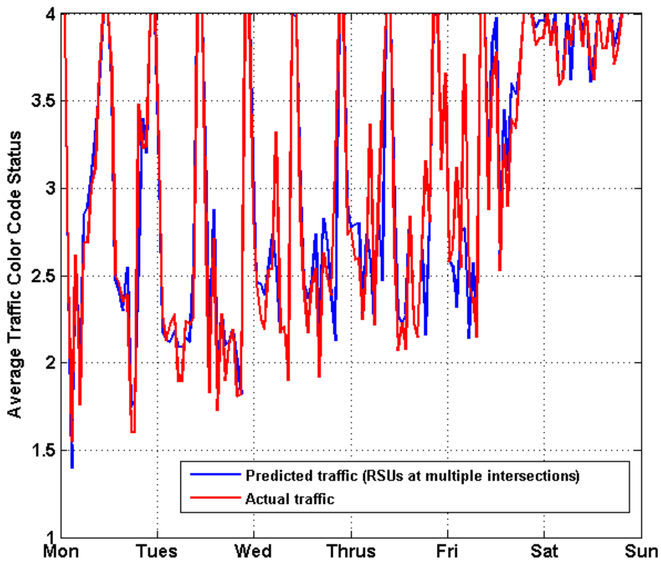
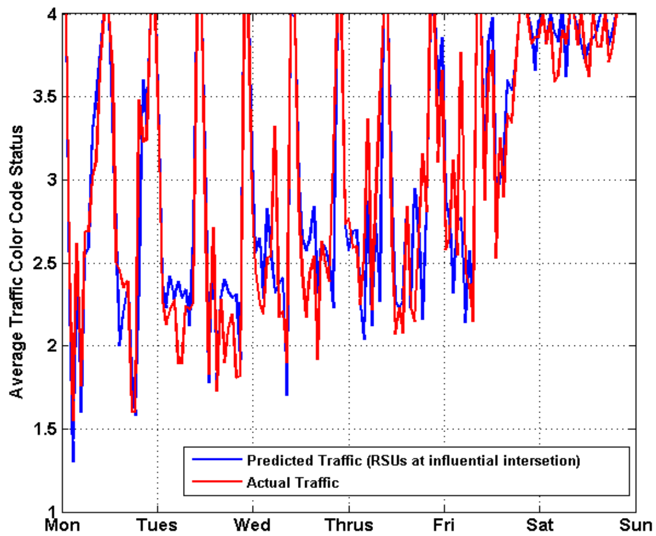


Figure 3.18 Traffic prediction Area



(a)



(b)

Figure 3.19: (a) Traffic prediction with multiple RSUs (b) Single RSU at influential intersection

Thus, two important deductions are inferred from this section.

1. Firstly, the proposed IIA-ORD scheme is a justified model in supporting different traffic regulation schemes with reduced RSUs without compromising on coverage, connectivity or QoS issues.

2. Secondly, as long as the traffic regulation-based applications are made independent of the number of RSUs, they can be easily deployed in the IIA-ORD model with high accuracy levels.

3.3 An Energy-Efficient RSU Operating Scheme

Smart controlling of Roadside Unit (RSU) is possible by predicting urban traffic to minimize network resource consumption by enhancing energy efficiency in a great extent without interrupting the service. Suitable traffic prediction helps the central controller to change dynamically the RSU status from standby to active mode as switch off and on mode. Performance evaluation exhibits the effectiveness of such RSU-based intelligent transportation system (ITS).

3.3.1 Proposed Work

In Figure 3.20, we present the reference system architecture where set of mm wave based RSUs are deployed and controlled by central controller. Each vehicle has two communication interfaces one for LTE communication with controller and another mm wave paradigm for mm-RSUs. Traffic network is represented by directed graph $G = (V, E)$. V is the junction set $[v_1, v_{2,} \dots, v_N]$ and E $[E_1, E_{2,} \dots, E_N]$ is the connecting roadways between them. $R = \{R_1, R_2, \dots R_q\}$ is the set of mm-RSUs having equal transmission range are uniformly positioned throughout the network. The coverage overlapping area of two neighbouring RSUs are too less to consider. $TI_i(t)$ is the traffic index of a road in a particular time frame which determines the congestion status of a road by the threshold value parameter μ. Central controller observes the predicted traffic status of all the edges at each timeframe and controls RSUs On/Off status.

$$s_i(t) = \begin{cases} 1, & TI_i(t) \geq \mu, \forall t \in T \\ 0, & Otherwise \end{cases} \tag{3.14}$$

Here, $s_i(t) \in \{0,1\}$ is the binary variable used to determine the RSU's active or standby status by the controller at timeslot t. $s_i(t)$ will be 0 when predicted traffic index is less than the predefined threshold and RSU will be in standby mode. For traffic prediction controller uses LSTM framework as it is suitable for time series sequential data prediction. Historical and real-time traffic density, speed of every connecting roadway are used to forecast future traffic index with the intention of minimum prediction error [124]. Algorithm 1 illustrates the basic prediction algorithm of LSTM.

Algorithm: 1

1. Initialize & normalize dataset $TI_{lstm_i} = Concatenate\{speed_i, density_i\}$
2. Initialize LSTM network with input vectors
3. **For** iteration = 1 to $iteration_{max}$ **do**
4.   **For** each R_i **do**
5.   **For** each E_i **do**

6. Predict traffic data using LSTM module

7. Calculate loss RMSE $\{\sqrt{\sum_{i=1}^{n}\frac{(actual-predicted)^2}{N}}\}$

8. **End For**

9. **End For**

10. **End For**

Energy efficiency τ of the system during total considered time T_{total} is calculated by

$$\tau = \frac{P_{active}T_{total} - P_{active}T_{active}}{P_{active}T_{total}} \quad (3.15)$$

Where T_{active} is the time when RSU is in active state and P_{active} is the consumed power of the RSU is active state.

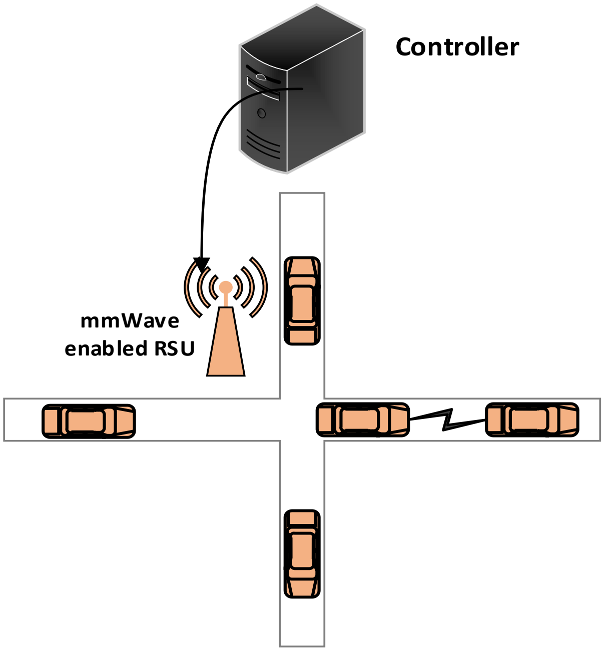


Figure 3.20: Reference System Architecture

3.3.2 Performance Evaluation

We validate the proposed framework performance using Bara bazar area map from Kolkata city. Figure 3.21 demonstrates the simulation scenario. We used SUMO to generate traffic data on road geometry [131]. Simulation parameters are summarized in table 3.6.

Figure 3.21: Screenshot of considered experimental region OSM map [132] and simulation

Figure 3.22 and 3.23 depict the proposed scheme's performance in terms of number of active mm-RSUs and energy efficiency over the number of vehicles for different mm-RSU coverage ranges. In Figure 3.22, if transmission range is less, then more number of RSUs are required to be active when the number of vehicles are increasing.

If transmission range is less then coverage area is also reduced. When we can handle larger area traffic through less number of RSUs to minimize their spent energy by prolonging their standby state through predicted traffic then energy efficiency will be enhanced. In Figure 3.24, it is shown that for lower transmission ranges, energy efficiency is reduced faster when number of vehicles are increasing.

Table 3.6. Simulation parameters

Parameters	**Values**
Area	$5Km \times 5Km$
Nodes and Edges	125 and 399
Vehicle length and safety gap	5m and 2m
Car following model	Krauss

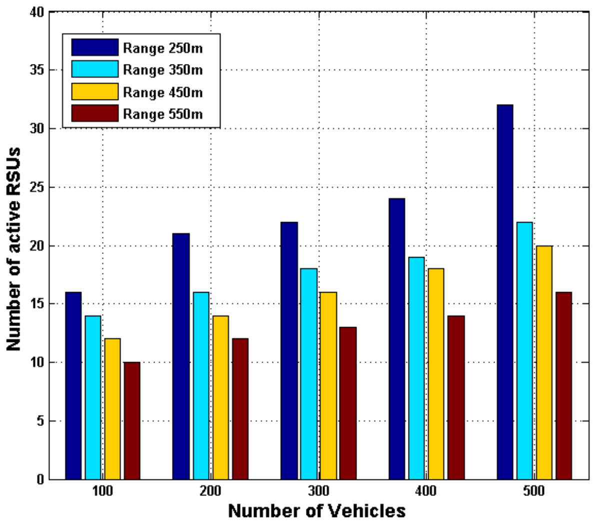


Figure 3.22: Number of on mm-RSUs with respect to number of vehicles for different RSU transmission range

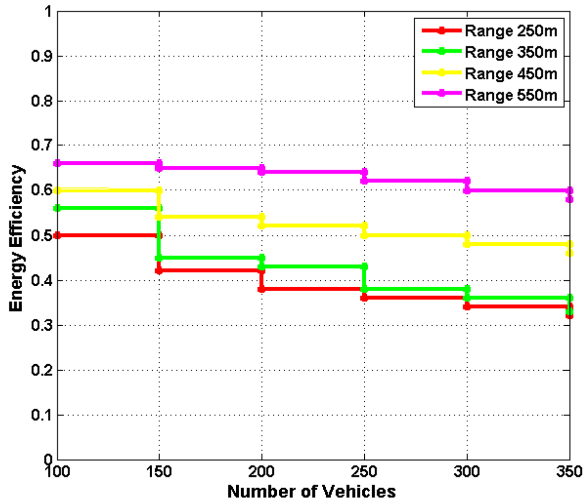


Figure 3.22: Energy efficiency with respect to number of vehicles for different mm-RSU transmission range

3.4 Chapter Summary

This chapter considers the challenge of optimal RSU deployment in VANET systems, specifically under the constraint that a higher number of RSUs may increase coverage at the cost of higher expenses and maintenance services. To this end, a new placement approach called Influential Intersection Analysis for optimal RSU Deployment is introduced that aims to solve this challenge using a four-phase methodology. While two phases deal with determining the static and dynamic centrality measures, the other two phases deploy respectively a modified weighted K-shell algorithm for influential region detection followed by execution of TOPSIS methodology for ranking different intersections under varying weights. In another novel contribution, a simulation framework based on the integration of different open-source simulation environments is designed for the evaluation and execution of the IIA-ORD scheme. In absence of well-documented traffic data particularly in the Indian context, the designed platform can be used to map and extract traffic congestion values from Google data and analyze these values with respect to different regions, days as well as time slots. Two-case studies involving the busiest intersections in the Indian city of Kolkata are chosen and the IIA-ORD model is deployed. Performance superiority is observed over existing works with respect to several performance indicators including coverage ratio, coverage time ratio, end-to-end delay, contacts per trip, packet delivery ratio, and number of RSUs. Finally, in one of the most significant contributions of this work, the proposed IIA-ORD model is validated by designing a novel stacked BiD-LSTM-based traffic forecasting application and executing it under the

IIA-ORD model. It is clearly observed that even with reduced RSUs, IIAORD succeeds in maintaining a high accuracy level while forecasting traffic congestion. Both the model as well as the simulation environment serve as a platform for further research in this domain of VANET and related Intelligent Transportation System based solutions, especially when dealing with sparse data as in the Indian context.

In this chapter, we also have explored an energy-efficient on/off switching approach for 5G enabled mm-RSUs in a vehicular simulation environment depending on the traffic parameters. It is possible to optimize energy efficiency even further by dynamically handling power of the mm-RSUs and increase the accuracy of traffic prediction by incorporating weather and road accidents information. For a congested city like Kolkata this method will be effective for energy saving.

❖ Publications from this chapter

1. Sreya Ghosh, Iti Saha Misra, Tamal Chakraborty, "Optimal RSU deployment using complex network analysis for traffic prediction in VANET", Peer-to-Peer Networking and Applications. 2023 Mar; 16(2):1135-54.

2. Sreya Ghosh, Iti Saha Misra, "An Energy Efficient RSU Operating Scheme for 5G Enabled Intelligent Vehicular Networks|", In 2023 8th International Conference on Computers and Devices for Communication (CODEC) 2023 Dec 14 (pp. 1-2). IEEE.

4

Quality of Service Improvement of VANET Routing

Quality of Service Improvement of VANET Routing

Outline of the Chapter:

4.1 Introduction

"*Look deep into nature, and then you will understand everything better*." —
Albert Einstein

After suitably developing RSU deployment framework in Chapter 3, the next focus is the detailed analytical observation of VANET routing algorithms followed by suitable optimization algorithms to achieve optimal quality of service performance. Vehicular ad-hoc network (VANET) is an emerging Intelligent Transportation System (ITS) technology that facilitates Vehicle-to-vehicle and vehicle-to-infrastructure communication. It enables several vehicular safety applications, such as collision avoidance, road condition broadcast, emergency warning, and lane-changing scenarios [137]. Now a day, because of rapid implementation of these applications, VANETs are experiencing significant advancements, alongside developments in autonomous car technologies. To ensure road efficiency and safety of the transportation system, the Federal Communications Commission (FCC) has allocated 75 MHz of spectrum in the 5.9 GHz band for dedicated short-range communications (DSRC) which are exclusively used for vehicle-to-vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication [138].

Unlike MANET, VANET has unique attributes, including self-organizing capability, high mobile nodes, road infrastructure limitations, a wide-ranging network, etc. [139]. Although

VANET achieves remarkable outgrowth, many significant challenges remain, such as medium access control (MAC), security, routing, quality of service (QoS), etc. This research primarily concentrates on designing routing protocols that can handle high-velocity vehicular nodes in VANET along with QoS constraints [140].

Vehicular ad hoc networks (VANETs) are the advancement of mobile ad hoc networks (MANETs), dedicated to wireless connectivity between vehicles, which is a property of intelligent transportation systems. Vehicles communicate in multi-hop as well as single-hop manner to transmit information from the source vehicle to the destination vehicle [141]. VANETs are applied to enhance commuter safety, congestion control, emergency warning, efficient path planning to reduce travel time, and so forth [142]. Vehicles communicate traffic status through control packets to be aware of nearby accidents and congestion. To achieve safety for drivers and commuters VANET has to distinguish false information producing from attackers. A more secure vehicular network can ensure less human casualty and fuel consumption which manages to achieve crucial improvement in the transportation system [143] [144]. To accomplish the aforementioned goals roadside units are the most significant backbone infrastructure of ITS. For data transmission, RSUs exchanged information with vehicle equipped On board units (OBU) and application unit (AU) that is mounted in vehicles to provide safety applications. AU can communicate with OBU in both wired and wireless manner. Hence, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication is achieved [145] [146]. Data transmission takes place through unicast, multicast, and broadcast depending on the scenarios. VANET transmits control packets as well as data packets and mostly depends on broadcasting, so it inevitably suffers from broadcast storms that consume unnecessary bandwidth [147]. Best route discovery generally depends on the successful transmission of control packets. However, in reality, smaller-sized control packets do not give assurance of successful delivery of data packets [148]. As the communication environment is heterogeneous then the routing protocol has to be capable of dealing with hybrid topologies. When routing protocols only rely on the local best route for data transmission then it is not efficient when the route is not optimal globally. If the nodes do not know neighbour node paths, then their path can be overlapped [149]. As information propagation is important to achieve successful ITS, the implementation of an efficient routing protocol is a very intriguing topic for researchers. Precisely, reduced network latency and increased packet delivery ratio ensure QoS, which warns drivers about road conditions hence road accidents can be controlled [150]. A highly mobile vehicular environment makes VANET routing difficult and prone to link failure. Using cache-enabled RSUs and OBUs is an effective way to make data dissemination punctual and safe [151]. RSUs cache memory collects OBU-generated information to transmit it to other OBUs and other RSUs through backhaul communication [152]. Since the caching capability of RSUs is much greater than OBUs, storing route information in RSUs is much more effective than in OBUs. Vehicles can retrieve the information from RSUs through V2I communication [153]. When cached route information is used in V2V communication, which makes routing fast, and reduces network overhead.

Routing protocols are mainly categorized into topology-based routing protocols and geographic routing protocols. The first one utilizes network topology information to connect vehicular nodes and another one incorporates location-based services to route the data packets in the network. In Chapter 2 background literature on topological and geographical routing protocols are elaborated in detail.

Topology-based routing decides paths based on the underlying topological structure of the network. Although they target to achieve accurate destinations, shortest discovered paths and reduced rate of packet dropping their performance deteriorates due to increased delay, overhead, and unreliable routes. However, geographical routing protocols utilize location-based services to select the path from source to destination for data transmission. This feature enhances route reliability and decreases packet-dropping probability. Still, end-to-end delay is a concern for this routing category. Static road maps are used to build routes, which is unable to find the accurate position of the destination. The above-stated categories of routing protocols are related to classical computational methods, which are less practical, complex and not suitable for extensive vehicular networks [154].

Presently, bio-inspired routing protocols for vehicular networks acquire significant attention because of their capabilities including scalability, ad-hoc nature, adaptability, robustness, and many more [155]. Bio-inspired approaches are preferable in broad vehicular networks because of the resemblance between process of finding packet forwarder vehicle and searching food sources for animals or swarms. These algorithms are less complex to solve computational problems. Their adaptable and self-organizing nature makes them a great choice to deal with the recurrent changes of vehicular network [156]. Among the huge explored algorithms ant colony optimization (ACO) based routing protocols are rapidly explored. A detailed description is categorized in the chapter 2 literature survey in section 2.3. In an urban VANET environment, packet forwarder is always present but for successful delivery route discovery from source to target is necessary. For that purpose, control packets are broadcast by the vehicles, which increase network overhead. First contribution of this chapter delivers an ACO based VANET routing algorithm that minimizes control packet broadcasting and assure optimum result when vehicles are out of the range. The next contribution optimizes the shortcomings of ACO based algorithms and proposes a novel bio-inspired algorithm named as canine olfactory route-finding algorithm (CORFA).

CORFA manages the process of route finding for VANET, which is an integral part of ITS that, are further used for data packet transmission. The proposed approach is a nature-inspired; meta-heuristics approach that considers a canine's exceptional olfactory ability. An optimization algorithm is used for the improvement of routing. This algorithm is inspired by canines' communication capabilities with each other. They sniff, bark, and pass the message to each other. Their barking process is different for specific information and loudness intensity helps them to guide about the distance of the target. A dog's most powerful sense is its sense of sniffing through which it can recognize not only the present status of the environment but also the past known phenomena. Dogs transmit the message to each other by barking and the level of loudness denotes the distance from the target. Even they can categorize their barking according to specific information [157], [158]. Here, the fittest member for packet forwarding is decided in terms of the barking coefficient. Higher the barking intensity denotes the node is more appropriate for forwarding the packet. Performance is compared with previously implemented VANET routing protocols in terms of packet delivery ratio, network latency, throughput, and overhead.

4.1.1 Contributions of this chapter

Key contributions of the proposed research in this chapter are listed below:

- An ACO based algorithm named as reduced route overhead by ACO (RRO-ACO) is proposed to avoid such situation when link failure occurs due to any unwanted event like accidents as a result data packets cannot be forwarded. The proposed routing algorithm is focused on searching the optimum QoS path between the source and destination where minimum hop count and delay can be assured.
- Sending packets requires more energy than receiving, so this algorithm reduces packet transmission and routing expenditure.
- The performance analysis is done by using SUMO (Simulation of Urban Mobility) flowed by Network Simulator (NS 2.34) then compared with RAGR [58] and RDACO [60].
- Further, we take into consideration about the limitations of ACO based algorithms and a novel bio-inspired algorithm is introduced that outperforms in comparison with ACO

based routing algorithms. The mathematical model of proposed method is presented in this chapter. Through sniffing movement previously, the canines memorize explored environment and they have used barking to communicate with each other. This unique feature can effectively incorporate in VANET environment.

- We propose a framework that utilizes the RSU cache memory for VANET routing. RSUs can communicate with other nearby RSUs through backhaul link. Cluster of vehicles are moving in a predictive uniform manner. When communicating vehicle requires a previously established route, the nearest RSUs can provide it from their pre-cached route table. This approach can notably reduce link failure scenarios, route discovery delay, and route maintenance expenditure.
- When route is not available in RSU cache memory, route discovery is occurred by restricted control packet broadcasting. All the link and timestamp details are analyzed to build the best route as well as the alternate routes. This will reduce routing overhead and ensure successful packet transmission if link failure happens.
- A series of experiments are run by utilizing a quality-of-service-based fitness function to prove the optimization capability of CORFA. The convergence is compared against significant bio-inspired optimization algorithms namely PSOR [66], CSO-GR [69] used in VANET.
- Finally, we perform comprehensive simulation analysis on the real map and observe the network performance based on varying traffic density, source-to-destination distance, data packet size, and vehicular speed. The simulation outcomes are illustrated and studied in detail. Experiments are conducted to compare CORFA with both geographical and topological routing protocols. Packet delivery ratio, latency, overhead, and throughput performance are compared with the existing geographical routing protocols namely, RAGR [58], RDACO [60], EGSR [63] and topological routing protocols namely, OLSR [48], AOMDV [53], ACO-AODV [61].

4.1.2 Chapter Organization

This chapter is structured in the following manner where in section 4.2 the ACO based protocol RRO-ACO is illustrated. In subsection 4.2.1, system model is defined and 4.2.2 presents the results analysis. Section 4.3 elaborates the novel bio-inspired algorithm CORFA. In subsection 4.3.1, first we illustrate the system model and then represents the operation principle in section 4.3.2. In subsection 4.3.3, we validate supremacy of our proposed algorithm through extensive performance analysis. Finally, we conclude the chapter with the summary section 4.4.

4.2 Reduced Route Overhead by Ant Colony Optimization Algorithm

The relevancy of VANET has increased enormously in the last decade. This field of intelligent transport system has to deal with dynamic vehicular traffic with high mobility that makes multi-hop communication links more vulnerable and unreliable. To encounter the matters like delay, packet dropping, this research work proposes a novel routing algorithm named as Reduced Routing Overhead using Ant Colony Optimization (RRO-ACO) with ACK packet broadcasting. Using Ant Colony Optimization (ACO) vehicular nodes can forward packet in more educated manner and use of ACK packets reduce redundant packet transmission. Traffic simulator SUMO and network simulator NS 2.34 are used to compare proposed algorithm with existing (Route Discovery ACO) RDACO and RAGR (Road Aware Geographical Routing). Results show that proposed method (RRO-ACO) outperforms the existing algorithms in terms of the QoS parameters like throughput, packet delivery ratio and network latency.

4.2.1 System Model

A. Brief overview of ACO

Ant's capability for searching the shortest path from their nest to a food source is denoted as ACO. The most reliable swarm intelligence-based technique is fundamentally motivated from the behaviour of insects and animals [159]. In searching for food, ants leave chemical substance throughout the route called Pheromones to mark the route they have passed. Through the released pheromones, following ants can get the clues about the shortest path to the food. Ants are attracted by the high concentration of pheromone, which evaporates over time. As shortest path retains the high pheromone concentration than the longer path, ants can easily find the optimum path [160].

B. Algorithm Description

The following assumptions have been taken to design the proposed algorithm.

- Each vehicle is equipped with GPS and On Board Unit (OBU) module. The OBUs send vehicle data including GPS coordinates, velocity, route to the next node, and infrastructure.
- Vehicles broadcast its present position with the help of periodic beacon so that vehicles within the coverage can forward the data towards destination.

- Signal propagation loss by buildings and obstacles are not considered for this scenario.
- Not all nodes receive data packets at the same time from the source when it broadcasts.

Source vehicle wants to transmit packet to the destination vehicle for that it broadcasts forward ant packets as depicted in Figure 4.1. Ant packets do not repeat the nodes that have already been covered and disappears when hop count limit crosses the maximum determined value. Hop count is validated and the pheromone trail is updated when the node receives a forward ant packet. Total amount of pheromone related with the whole route is similar to the individual pheromone of the intermediate links of the whole route. Whenever next hop vehicle B receives the packet from Source; it broadcasts and next layer of vehicles receive and notify through an acknowledgement (ACK) signal with packet identification to the previous layer. As sending takes, more energy than receiving, vehicle A and C do not transmit data packet to the next layer. Simultaneously from the next layer packet transmission occurs through the best quality route only. When next hop vehicle is not available or difficult to reach due to link failure between hops then it is impossible to forward packet to the next hop. As shown in the Figure 4.2 from node D next hop F is out of the range due to some catastrophic event or coverage issue. Then node D sends a unicast message to the nearest Roadside Unit (RSU) with the packet through V2I communication. Then RSU broadcasts the packet and creates pseudo ant vehicle to complete the packet transmission. This algorithm can handle data forwarding in dense traffic region as well as sparse traffic region where significant amount of vehicle is not present. After reaching the destination forward ant packets convert into backward ant packets. Backward ant packets visit to the source vehicle by following the same process. As depicted in Figure 4.3, the former path traversed by the forward ant may not be in the exact location for the later one. The diversity between the list of discovered nodes by forward ant and backward ant vehicles find out the stability of the routing path.

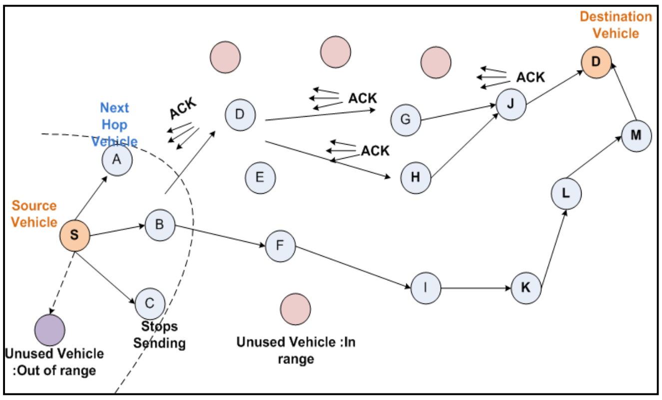


Figure 4.1 Reduced route formed by Forward Ant Packet

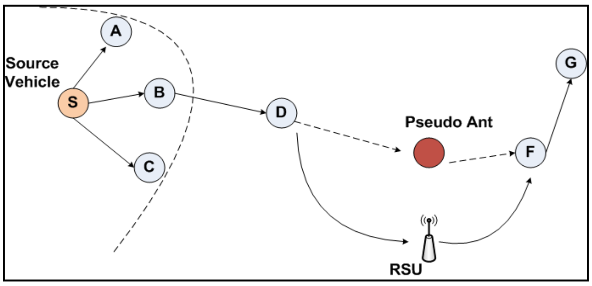


Figure 4.2 Link Failure Scenario

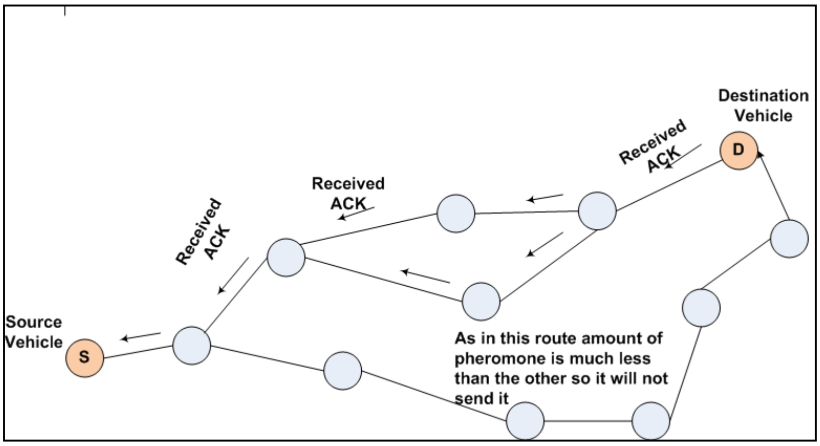


Figure 4.3 Route created by backward ant packet

C. Operation Principal

Location-based services are used to find the exact location of the destination and the current forwarder. If destination is out of coverage area, then current node searches the best suited route to forward the data to destination otherwise it sends the data to destination directly. If the current forwarder finds the next hop node it routes the data packet otherwise it sends a unicast join request to the nearest RSU. RSU created a pseudo-ant vehicle to complete the route.

Vehicles send Ack packet after receiving ant packet. After calculating, the distance from own position to the destination by GPS, global pheromone will be updated. If the destination is reached forward ant to backward ant transformation happens and returns through the reverse route to the source. When source receives backward ant packets, it determines the shortest route by global pheromone level and sends data to the destination. Which route shows the similarity between forward and backward ant considers as most stable. Data transmission follows the discovered route. In Figure 4.4, flow diagram for the proposal is given.

D. RRO-ACO Mathematical Modelling

Pheromone disperses throughout the ant travelling path so that future ants can select a path in a much-more educated manner. If forward ant packets' transmission delay to the destination are below the threshold limit, then only it converts into backward ant.

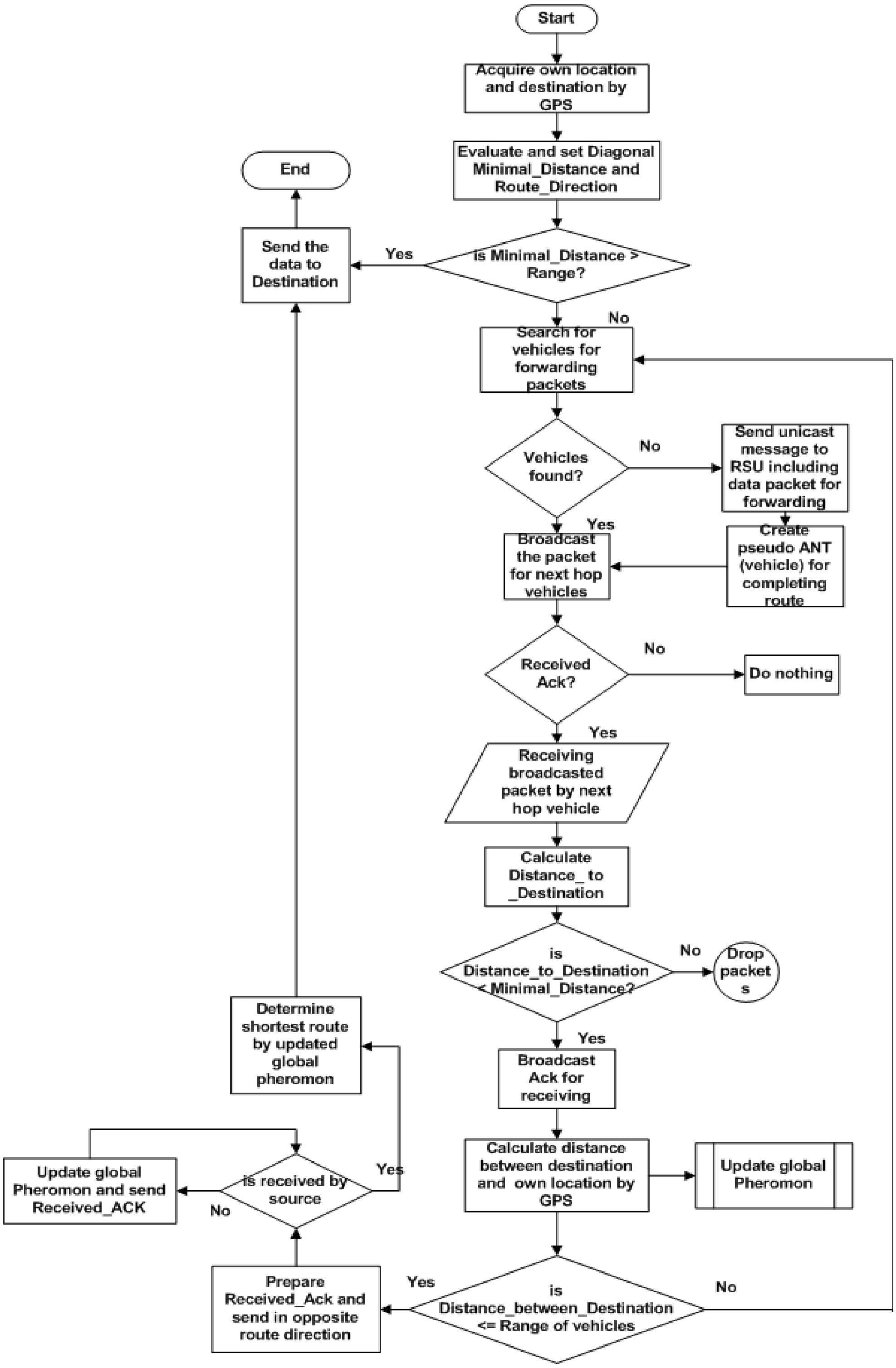


Figure 4.4 Flow Chart of the proposed method

Backward ant mainly determines the route stability. Both the ant packets maintain different ant tables so that after returning to the source best route can be selected through evaluation. The link quality or link lifetime depends upon the vaporization level of the pheromone as it differentiates with time. The pheromone is placed on a particular link (ψ_{BF}) is estimated by the sum of link stability and the probability of getting packets successfully [60].

$$\psi_{BF} = ls_{BF} + P_{pkt}^{BF} \tag{4.1}$$

ls_{BF} is the link stability between nodes B and F. P_{pkt} is successful packet getting probability. The vehicle is placed in the middle of the transmission range where direction matched with packet flow and with minimum velocity gets highest importance for link quality calculation [161]. P_{pkt}^{BF} is the ratio of ant packets received by the next hop vehicle to ant packets sent by the previous vehicle,

$$P_{pkt}^{BF} = \frac{P_R^F}{P_T^B} \tag{4.2}$$

Let ant 'a' is moving from link B to link F the probability of movement of ant 'a' is given by,

$$P_{BF}^{a} = \frac{[\tau_{BF}(t)]^{\alpha}[\gamma_{BF}(t)]^{\beta}}{\sum_{F \epsilon allowed\ a}[\tau_{BF}(t)]^{\alpha}[\gamma_{BF}(t)]^{\beta}} \tag{4.3}$$

where, $\gamma_{BF}(t)$ is adaptive coefficient and $\tau_{BF}(t)$ is pheromone density level. $0 \leq \alpha$ and $\beta \geq 1$ is parameter to control the influence of $\tau_{BF}(t)$ and $\gamma_{BF}(t)$ respectively. $\tau_{BF}(t)$ is given by,

$$\tau_{BF} = (1 - \rho + \eta)\tau_{BF} + \rho\tau_0\eta \tag{4.4}$$

ρ is the coefficient of vaporization of pheromone and η is pheromone stability factor due to use of RSU for what link failure reduces. τ_0 is the primary pheromone value for link B and F. Total pheromone level can be achieved by the sum of each arc travelled by the ant packet. When the ant packets confirm route a global updating process is done so that the best stable path can be selected [147]. Global pheromone quantity for entire path is denoted by,

$$\tau_G = (1 + \eta)\tau_G - \rho(\tau_G \cdot \eta - \frac{\eta}{Delay} - \eta \cdot Stability) \tag{4.5}$$

while, delay is defined by time taken by forward ant packet starts visiting from source to backward ant received by the source. Stability means how much similarity is there in between the forward and backward ant tables. The number of packets needed to be exchanged for our proposed algorithm is given by,

$$\sum_{i=0}^{n}(V_i + c_i) \times 2 \tag{4.6}$$

Where is V_i number of vehicles sending packets at each hops, c_i is the additional vehicle received the packet. The packet number is doubled because of the ACK packets. In case of RDACO [58] the Packet exchanged number is,

$$\sum_{i=0}^{n}(VA_i) \times F_i \tag{4.7}$$

Where, VA_i is all the vehicles at the hop. F_i is retry or failure transmission of packet. More number of vehicles is taking part in transmission more the failure rate is. The route with maximum pheromone deposited is most stable and fastest is elected as best route for data transmission. Within predefined time limit when path is not available, vehicles broadcast forward ant after a while.

4.2.2 Results and Discussions

Routing performances of RAGR [58], RDACO [60], and our proposed RRO-ACO are analyzed in Network Simulator NS-2.34. Simulation parameters used for implementation are listed in Table 4.1. Vehicle node mobility is generated using open source traffic generator SUMO. We set a map of the Kalighat area of Kolkata city, which is one of the most congested road traffic areas extracted from the open street map in Figure 4.5. The trace file generated in SUMO is directly used in NS 2.34. Using the parameter metric in Table 4.1, the results are generated and analyzed.

TABLE 4.1. Simulation Parameters

Parameters	**Values**
Simulator used	NS 2.34
MAC Protocol	802.11p
Transmission Range	300 m
Data Packet size	512 Bytes
Map Layout Area	3000×1200 m^2
Simulation Time	200 sec
Packet Transmission Rate	1 packet/sec
Number of Vehicle Nodes	100-200
Speed of Vehicles	15-20 m/sec
Propagation Model	Nakagami

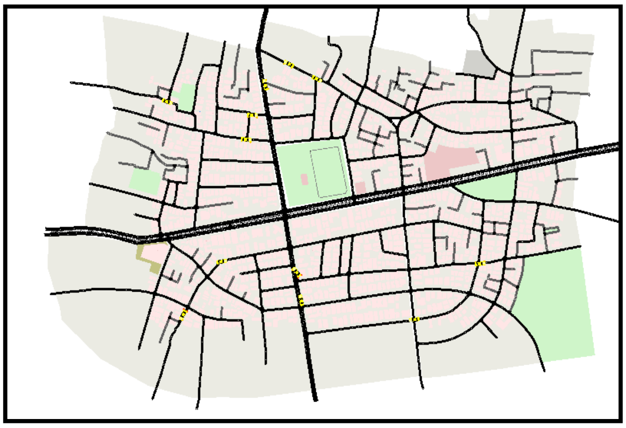


Figure 4.5 Fragmented map used for SUMO simulation.

A. Throughput for traffic densities

Data packets transmitted within a particular time duration from one position to another is denoted as throughput. From Figure 4.6 it is seen that our proposed RRO-ACO has outperformed with traffic density variation from 100 to 200. As there is less packet transmission and link failure in the case of RRO-ACO than RDACO, packet loss is reduced and average throughput is increased by 16.33%. In the case of RAGR path is not known prior to data transmission, which makes the path less reliable and causes more packet loss than RDACO and RRO-ACO.

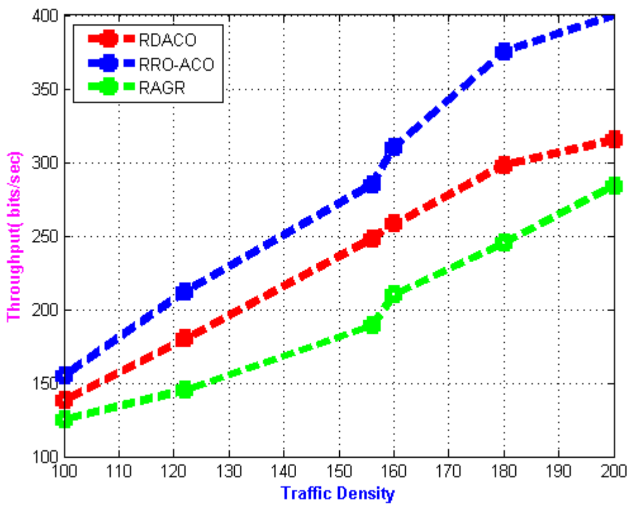


Figure 4.6. Throughput of RRO-ACO with existing RDACO and RAGR in the presence of different traffic densities.

B. Packet Delivery ratio for different Traffic Densities

Packet Delivery Ratio is measured by the ratio of packets received by the destination to the packet sent by the source. In terms of packet delivery ratio, RRO-ACO performs better due to selective transmission with the help of ACK packets as shown in Figure 4.7. Therefore, in case of RRO-ACO same packets are not re-transmitted at a time, which reduces transmission energy, congestion and optimized packet delivery.

C. Network latency with changing traffic densities

Network latency is the time required for delivering a data packet from source to destination. Low latency means packet transmission with optimum route in a delay measurement parameter. Figure 4.8 depicts that RRO-ACO shows low latency while compared with RDACO [58] and RAGR [56]. High delay occurs in case of RDACO because of same packet retransmits more than once which creates congestion and delay. In case of RAGR optimal road selection depends upon multiple routing metrics like direction, distance and traffic density which makes the data packet forwarding process more complex and delayed.

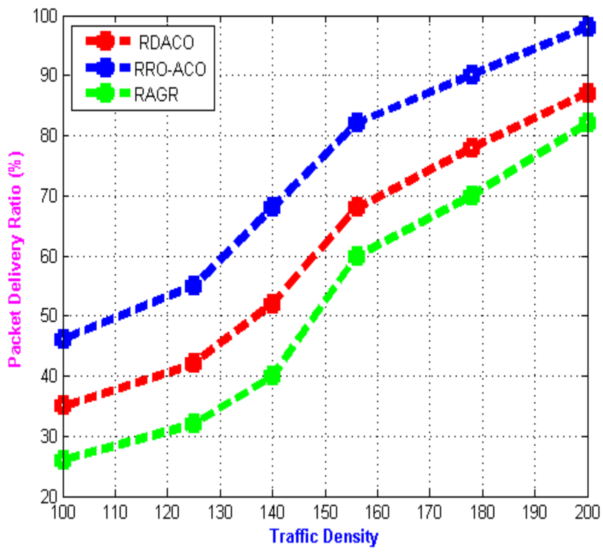


Figure 4.7. PDR analysis of RRO-ACO with RDACO and RAGR

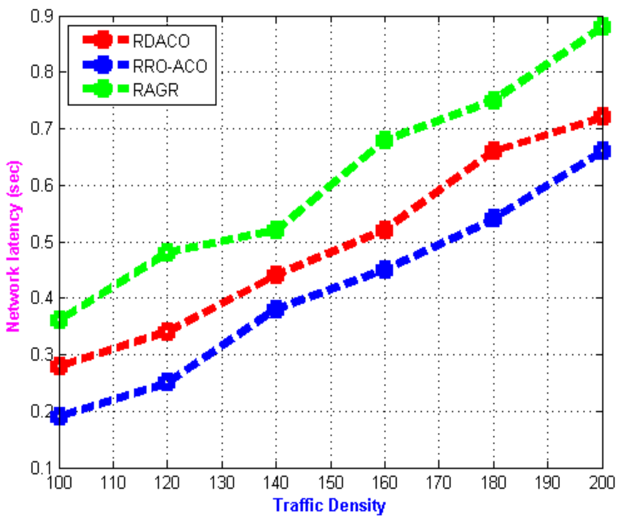


Figure 4.8: Network Latency analysis of RRO-ACO with RDACO and RAGR

4.3. Canine Olfactory Route-Finding Algorithm

QoS aware Vehicular Ad hoc Network (VANET) routing protocols has enormous capability to assure the increasing demand of delay-sensitive vehicular applications for intelligent transportation. Ad hoc nature of VANET makes the communication between vehicle to vehicle and vehicle to infrastructure vulnerable and prone to link failure. Bio inspired algorithms is a promising technology to address VANET routing issues.

Table 4.2 Percentage improvement of QoS parameters with respect to traffic density

Traffic Density	**Percentage improvement of Proposed RRO-ACO Over RDACO and RAGR**						
	Throughput Increased		***PDR Increased***		***Network Delay Decreased***		***Comment***
	RDACO	***RAGR***	***RDACO***	***RAGR***	***RDACO***	***RAGR***	Better QoS performance achieved
120	17.77 %	46.20 %	30.95 %	42.85 %	-33.33 %	-47 %	
160	15.67 %	47.61 %	26.15 %	36.66 %	-22.05 %	-33.82 %	
180	19.04 %	53.06 %	25 %	28.57 %	-15.78 %	-28 %	
200	12.85 %	40.84 %	12.64 %	19.51 %	-19.10 %	-25 %	

In this research, Canines exceptional ability to evaluate the environment, memorize it, and pass the message to the deserving neighbour makes them a great choice to model their behaviour for VANET routing. Canine Olfactory Route-Finding algorithm (CORFA) is being proposed and implemented in VANET environment. As data and their optimal route of transmission play an important part in fast changing network topology, caching is a favourable methodology to enhance routing performance. Road Side Units (RSUs) are the fundamental elements of intelligent transportation infrastructure, which can carry out information dissemination task efficiently. Already traversed and discovered routing paths in recent past can be cached in RSU's storage and through backhaul can be circulated to neighbour RSUs as well. Vehicles movement pattern is predictable and in dense urban roadway group of vehicles follows uniform speed throughout the road segment. In a case when the vehicle requests same routing path, RSUs can provide them from their cache, and data transmission occurs *without the route discovery and maintenance*. Recent studies revealed that VANET suffers from broadcast storms due to excess control packet forwarding. Our proposed approach controls generation of control packet generation, which addresses the routing overhead issue. As the fittest vehicle from each hop is elected for data transmission, successful packet delivery is ensured. Destination creates alternate paths to encounter the link breakage scenario. Traffic simulator SUMO is used to generate mobility models and integrated with MATLAB for analyzing the performance of CORFA with efficient routing protocols such as RDACO [60], RAGR [58], and EGSR [63].

4.3.1 System Model

Data dissemination plays an important role to deal with rapid varying network topology. RSUs play an effective part in data management [162]. We have considered an area with set of deployed RSUs. Vehicles are equipped with On Board Units (OBU) that are used to communicate with RSUs. RSUs are enabled with caching capabilities, which is used to have a reduced routing overhead and increased QoS performance. Each RSU has cache capacity size of A with coverage area size C. RSU stores routing information in its memory for a certain time limit. When a vehicle arrives in its coverage zone, it requests for available routing content. A cluster of vehicles travelling on the same roadways towards the similar direction may have requirement of same contents that can be provided by the RSUs. If required route table is available in the current RSU then route discovery process is not necessary. Data packet forwarding can be done without any routing overhead that reduces delay in a great manner. In Figure 4.9, source vehicle wants to send data packet to destination vehicle. It broadcasts small control packet denoted as Sniffing packet with routing requirement details as a result RSU sends cached content that recalls previous successful data transmission path. Figure 4.10 shows message format of sniffing packet and the message format sent by RSU is given in Figure 4.11. Source vehicle checks the route availability and sends data following that route.

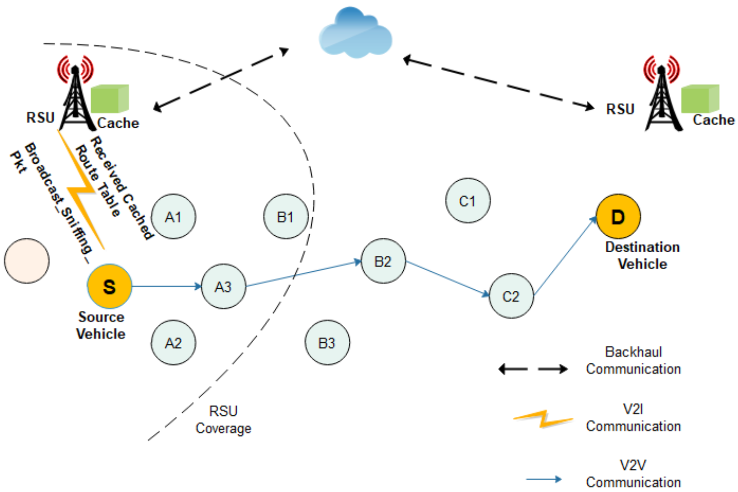


Figure 4.9: RSU caching process

Preamble	Source ID	Position	Sniffing Pkt Identifier	Broadcast Time	Permissible Delay	Hop count	Velocity	Neighbor IDs	Destination id	Checksum

Figure 4.10: Sniffing Packet Format

Preamble	Source ID	Destination ID	All routes	Best Route	Neighbor IDs	Hop count	Velocity	Checksum

Figure 4.11: Format of message Sent by RSU

Source vehicle wants to send data packet to destination vehicle when route is not available. In that case, route discovery is mandatory. Here in Figure 4.12, S broadcasts small control packet named as barking packet with time and link attribute (TLA) details. Figure 4.13 shows the message format of barking packet. Next hop recipient vehicles A1, A2 A3 receive it and stores with their respective received timestamp. Nodes broadcast the packet immediately and whenever others receive it, they have stopped broadcasting. Let, A1 broadcasts at first, next A3 also broadcasts, but A2 does not transmit any packet as it receives the packet from A1 and A3. Like this manner next slot of nodes B1, B2 and B3 receive the packet store in the TLA and transmit it to their respective next neighbour. In Figure 4.14, it shows that after packet reaches to destination vehicle node with all the TLA details, it elects the best route for data transmission and sends it to source. As the route details have the timestamp of each node, best node from each slot will be selected. In this scenario, as multiple route is discovered so in case of link unavailability when best route is not present, next best route will be considered for data transmission. In case of VANET, at time of data transmission the elected best route may not be present so in that case next best route is used.

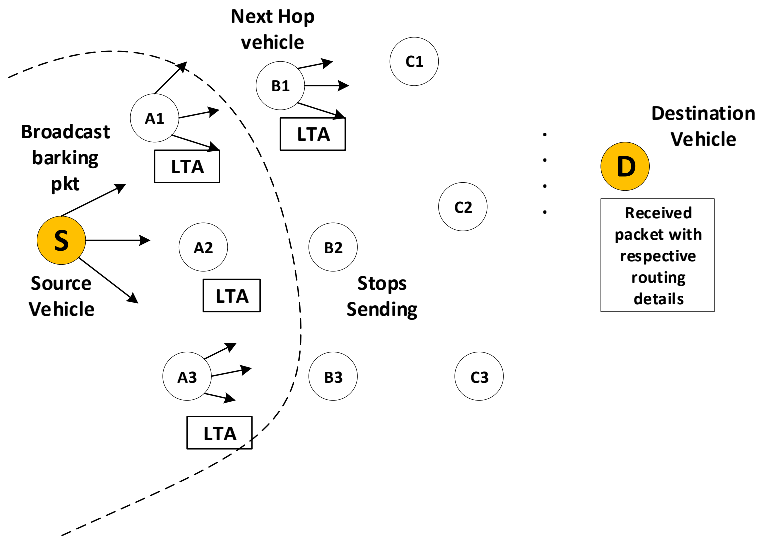


Figure 4.12: Route Discovery by Barking Broadcast Packet

Preamble	**Source id**	**Position**	**Barking Pkt**	**Broadcast Time**	**Delay**	**BW**	**Hop count**	**Velocity**	**Destination id**	**Checksum**

Figure 4.13 Barking Packet format

Table. 4.3 Packet Format Description

Field Name	**Explanation**
Source id	Source node id
Pkt Type	To identify the route
Delay	Permitted delay by the source node
BW	Minimum required bandwidth
Hop Count	Number of hops
Timestamp	To fetch the travelled time
Destination id	Destination node id

Assumptions:

We assumed that Each RSU has equal caching capability and coverage and is uniformly deployed over the experimental region. Each vehicle is OBU and GPS-assisted and connected through Dedicated Short-Range Communication (DSRC) protocol within a range of 150 m. Hence, its geographic location, velocity, and direction are easily available. Beacon packets are used to transmit network information and each node receives a packet from the source at different times.

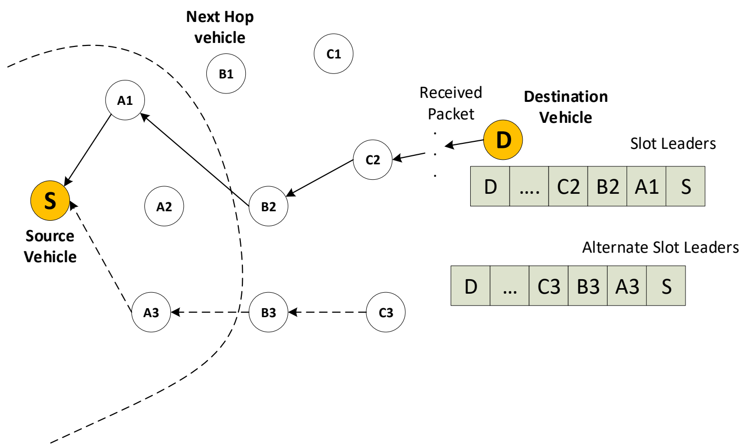


Figure 4.14 Best Route and alternate route creation

4.3.2 Operation Principle

The locations of vehicles are obtained with the help of location-based services. Overall routing algorithm is described in flow diagram, which is Figure 4.15. When source vehicle wants to transmit data packet to destination vehicle it finds out if the destination is within its coverage, if yes then data is sent directly to the target. When destination is not in the range then it checks route is already available or not. For immediate establishment of the route, it initiates query to nearest RSU. Algorithm 4.1 describes the caching mechanism followed to receive the route table. It applies the binary variables to check connection availability and routing content availability status. RSU sends the route details and data transmission takes place. When path is not available then fittest neighbour node discovery process starts. Route discovery is recommended to route original data efficiently. Packets coming from the vehicles within the request range is only taken care of otherwise packets are dropped. When nodes receive barking packet from the previous hop immediately it broadcasts to their next hop. Link quality and timestamp information is verified to select the next forwarder vehicle. Whenever vehicle receives barking packet from same hop count it stops broadcasting. The method continues until the desired destination vehicle is arrived. Whenever destination receives all the route details within the permissible delay limit it selects fittest member for each hop, which is shown in Algorithm 4.2. Barking coefficient considers link quality and successful packet receiving probability and verifies each vehicle from the hop count. However, because of the rapid topological changes discovered route is not always available at the time of data packet transmission. Because of the route details available at the destination, it creates alternate best route for link failure.

Algorithm 4.1: RSU Caching for Routing

Input: Vehicle set within RSU range at time t, Number of RSUs
Output: Pre-Cached Route Table

1. Obtain connection request from Source vehicle
2. Check $\alpha_{V,R}, \beta_{V,R}$ connection status and routing content availability status;
3. **While** True **do**
4. Get the set of routing tables need to establish data transmission path;
5.   **if** route details is fully received **then**
6.   RSU receives ACK
7. **if** *RSU cache* is full **then**
8. Discard Cached list
9. end **While**

Algorithm 4.2: Fittest Neighbor Selection

Input: Vehicle set $[v_1, v_{2,} \dots, v_N]$ as Population, Iterations [Current Hop count H_c, Destination Hop $H_{Destination}$]
Output: $V_{Highest}$ Fittest Solution of Population with highest (B_c^v)

1. Initialize Solution Space (Vehicle$_{position,velocity}$)
2. while $(H_c < H_{Destination})$
3.   **for** (i = 1 *to* N) **do**;
4.   Evaluate B_c for present Hop
5.   Rank the vehicles and elect best solution for forwarding
6.   end **for**
7. end **while**

a. Mathematical modelling for proposed CORFA in VANET

To design efficient VANET routing algorithm, the searching method for best fittest member in search space is mathematically modelled. CORFA operates in two phases. In phase 1, it is checked whether the search space is visited previously or not. If not then in the next phase search space is explored to determine fittest vehicle for message forwarding. Table 4.4 lists mathematical notations used to develop routing algorithm.

Phase 1

We have taken RSUs and arranged them by $R = \{R_1, R_2, \ldots R_q\}$, placed in the intersections. They are connected through high-speed LAN. These RSUs are enabled with computational and caching capabilities so that vehicles can retrieve required information from corresponding RSU.

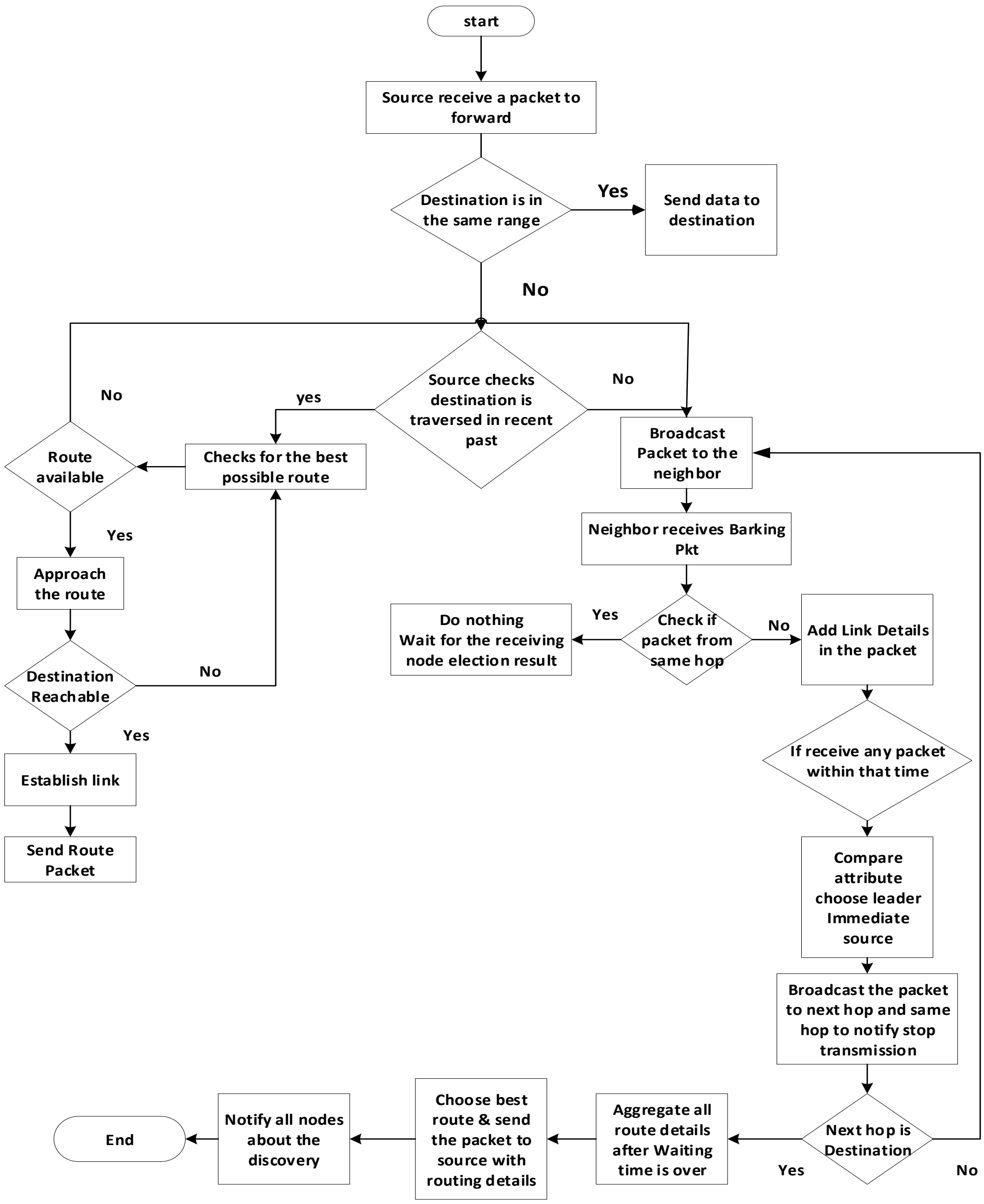


Figure 4.15 Flow Diagram of the entire routing process

- RSUs having equal transmission range and storage capacity are uniformly placed throughout the network. The coverage overlapping region of two consecutive RSUs is too less to consider. Vehicles can communicate with only one RSU at a timeframe. Timeframes are segregated in discrete time slots $t = (0, 1, 2 \ldots (t-1))$, vehicles can communicate with RSUs and vice versa. Only one vehicle is assisted in each time slot. When vehicles send request through control packets it transmits cached routing content through V2I communication link [151]. If communication rate is $CR_{V,R}(t)$ among vehicle V and RSU R then,

$$CR_{V,R}(t) = BW_{V,R}(t)\log_2(1 + \frac{P \times G_{V,R}}{N_0 \times BW_{V,R}})(t) \tag{4.8}$$

P is the transmission power, channel gain is denoted by $G_{V,R}$, $BW_{V,R}$ is the channel bandwidth between vehicle and RSU and N_0 represents noise power density.

- Binary variable $\alpha_{V,R}$ is used to determine the connection status between vehicle and RSU and $\beta_{V,R}$ denotes the routing content availability status.

$$\alpha_{V,R} = \begin{cases} 1, \textit{Vehicle and RSU are connected at time } t, \forall t \in T \\ 0, \qquad \textit{Otherwise} \end{cases} \tag{4.9}$$

$$\beta_{V,R} = \begin{cases} 1, \textit{routing table is available in cache at time } t, \forall t \in T \\ 0, \qquad \textit{Otherwise} \end{cases} \tag{4.10}$$

When ($\beta_{V,R} = 1$) RSU sends route information to allocated vehicle. As discussed in flow chart indexed as Figure 4.15 when routing information is not available in the RSU cache which indicates ($\beta_{V,R} = 0$), next phase of operation starts. In second phase fittest vehicles from each hop is selected for packet transmission.

Phase 2

- Transport network is denoted by directed graph $G = (V, E)$. V is the vehicles set $[v_1, v_{2,} \dots, v_N]$ and E $[E_1, E_{2,} \dots, E_N]$ is the connecting links between them. Let v_i and v_j are two vehicles on the route with initial position vector (X_{i_0}, Y_{i_0}) and (X_{j_0}, Y_{j_0}) with initial speed s_{i_0}, s_{j_0}. Let, the vehicles are neighbor means they are single hop away to each other. Gap between them is $D_{i,j}$ and communication range is $C_{i,j}$ [23]. Link exists when $D(i,j) < C$.

$$D_{i,j} = \sqrt{(X_{i_0} - X_{j_0})^2 + (Y_{i_0} - Y_{j_0})^2} \tag{4.11}$$

- Barking coefficient B_c^v decides fittest neighbor vehicle for packet transmission. B_c^v depends on link stability L_s, probability of successful message receiving $P_{i,j}^r$ and collision probability C_p. Value of this parameter determines next fittest neighbor for packet transmission. $V_{Highest}(B_c^v)$ denotes the fittest vehicle for data transmission.

$$B_c^v = \frac{L_s + P_{i,j}^r}{C_p} \tag{4.12}$$

Table 4.4: Mathematical Notations

	Parameters and Variables
R	Set of RSUs $\{R_1, R_2, \dots R_q\}$
t	Time is divided in slots $(0, 1, 2 \dots (t-1))$
$CR_{V,R}(t)$	Communication Rate between vehicle to RSU
P	Transmission Power
$G_{V,R}$	Channel Gain
$BW_{V,R}$	Bandwidth
N_0	Noise Power Density
$\alpha_{V,R}$	Binary variable to check V2I connection status
$\beta_{V,R}$	Binary variable to check route table availability in RSU cache
V	Set of vehicles $[v_1, v_{2,} \dots, v_N]$
E	Set of connecting roadway links $[E_1, E_{2,} \dots, E_N]$
$D_{i,j}$	Distance between vehicles
$C_{i,j}$	Communication range between vehicles
B_c^v	Barking Coefficient
L_s	Link stability
$P_{i,j}^r$	Successful message receiving probability
C_p	Collision Probability
$V_{Highest}(B_c^v)$	Fittest vehicle for data transmission
L_s	Link duration
H_c	Current Hop
N	Number of vehicles present in H_c
φ	number of vehicles stop transmission after receiving the control packet from H_c
$H_{adjacent}$	Number of interfering hops
γ	Fading parameter
$Pos_{Highest}(B_c^v)$	Position of fittest vehicle
$Pos_i(B_c^v)$	Position vector of the i^{th} vehicle
$V_i(B_c^v)$	Velocity vector of the i^{th} vehicle
α	Acceleration coefficient
W_i	Weight coefficient
PDR	Packet delivery ratio
$t_{End-end}$	End to end delay
RO	Routing Overhead
Th	Throughput

- Link between two vehicles v_i and v_j is formed at time instant t_0 when distance between them satisfies the condition $D(i,j) < C$ and breaks at time instant t_1 when $D(i,j) > C$.

Link duration is measured as $L_{D=}(t_1 - t_0)$. Link stability from one hop to another [34] is $L_s = \frac{L_D}{maxL_D}$. $maxL_D$ is the constant validity duration of routing table.

- Let, total packet transmission in current hop H_c is T_{actual} and T_{min} is the minimal transmitted packets to avoid collision. Then C_p will be given by,

$$C_p = 1 - \frac{T_{actual} - T_{min}}{T_{actual}} \tag{4.13}$$

Where, $T_{actual} = N - \varphi + \prod_{i=0}^{H_{adjacent}} \tau$. N is the number of vehicles present in hop H_c and φ is the number of vehicles stop transmission after receiving the control packet from the present hop. Vehicular network follows multi-hop communication so $\prod_{i=0}^{H_{adjacent}} \tau$ represents adjacent hop packets. $H_{adjacent}$ is the number of interfering hops.

- $P_{i,j}^r$ is calculated based on the distance between the neighboring vehicles. Here we have used Nakagami fading model [152] which is used to capture vehicular movement in urban environment [153]. With fading parameter γ,P^r will be,

$$P^r = e^{-\gamma(\frac{D^2}{C})} \sum_{i=1}^{\gamma} \frac{(\gamma\left(\frac{D^2}{C}\right))^{i-1}}{(i-1)!} \tag{4.14}$$

- According to the barking coefficient best candidate vehicle is selected for forwarding. $Pos_{Highest}(B_c^v)$ is the best position where barking coefficient is highest. α is the acceleration constant, $rand$ is the random number between [0,1]. $V_i(B_c^v)$ and $Pos_i(B_c^v)$ is the velocity and position vector respectively of the i^{th} vehicle in the search space. For accomplishing the message transmission, velocity and position of the following vehicles is denoted by $V_{next}(B_c^v)$ and Pos_{next} respectively and they are estimated

$$V_{next}(B_c^v) = V_{current}(B_c^v) + \alpha * rand(Pos_{Highest}(B_c^v) - Pos_{current}(B_c^v)) \tag{4.15}$$

$$Pos_{next} = Pos_{current} + V_{next}(B_c^v) \tag{4.16}$$

Fitness function f that is derived here is the aggregative minimizing function with normalized routing metrics values. W_1, W_2, W_3, W_4 are weight coefficients. PDR is the packet delivery ratio, $t_{End-end}$ is total delay for packet transmission, Th is throughput and RO is routing overhead.

$$f = W_1.(-PDR) + W_2.t_{End-end} + W_3.RO + W_4(-Th) \tag{4.17}$$

Subject to:

$$\sum_{i=1}^{4} W_i = 1, W_i \in (0,1)$$

$$dis(V_{next}, V_{current}) \leq D_{max}$$

Fitness function is designed to achieve maximize PDR and throughput and to minimize overhead and delay.

4.3.3 Performance Evaluation of CORFA

This section presents the performance evaluation of proposed algorithm and compares with existing efficient routing protocols based on several QoS metrics. System is implemented using the open-source traffic simulator SUMO [131].

- One of the crowded junctions of Kolkata city map is park circus area, which is imported from Open Street Map [132] in xml format, named as osm.xml. It contains overall streets, lanes and buildings, which creates a real time platform for simulation. Netconvert changes osm.xml file to net.xml. After network preparation phase, vehicle mobility is produced by ACTIVITYGEN package. It creates origin-destination pair for each vehicle that is saved in trips.xml. This part completes with DUAROUTER package where route file rou.xml is generated.
- Matlab is used to implement vehicular communication according to the proposed routing algorithm. To initiate incorporation between SUMO and MATAB, Traffic Control Interface (TRACI) is used, which is a TCP based server/ client architecture to allow access to interface with SUMO. Simulation procedure is depicted in Figure 4.16. Figure 4.17 shows the osm map and its imported version in SUMO.

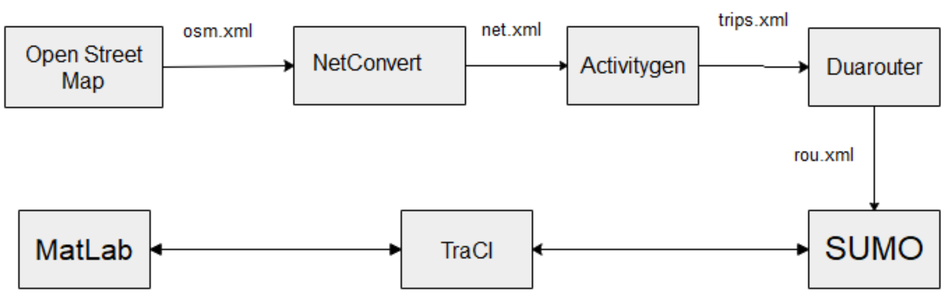


Figure 4.16 Simulation Framework

Figure 4.17 Open Street Map of the Simulation Area and Imported Version in SUMO

At first, physical layer radio model has been selected as IEEE 802.11p and Nakagami propagation model. Simulation parameters are listed in Table 4.5.

Table 4.5: Simulation parameters

Parameters	**Values**
Area	2000 m × 2000 m
Communication Range (V2I)	300 m
Communication Range (V2V)	150 m
Mac	IEEE 802.11p
Simulation Time	3600s
Carrier Frequency	5.89 GHz
Propagation Model	Nakagami
Traffic Type	CBR

b. Simulation Metrics

Packet Delivery Ratio is of number of successful data packets delivered at the destination to the number of data packets transmitted by the source [26] and is defined as:

$$PDR = \frac{\sum Received\ Packets}{\sum Sent\ Packets} \times 100$$

Throughput is measured as average number of data packets transferred between source and destination within a fixed period. Network congestion and adjacent channel interference affects throughput.

$$Throughput = \frac{\sum Number\ of\ received\ data\ packets}{\sum Simulation\ Time} \times Packet\ Size$$

Network Latency denotes the cumulative time taken for transmitting a packet from source node to destination. Here, it is measured in second. It includes transmission delay t_{trans}, processing delay t_{proc}, propagation delay t_{prop}. $t_{End-end} = \sum(t_{trans} + t_{prop} + t_{proc})$.

Routing Overhead is the packets sent for route discovery and maintenance. It is the ratio of total transmitted control packets sent across the network to number of received data packets.

$$RO = \frac{\sum Control\ Packets}{\sum Received\ Packets} \times 100$$

To evaluate supremacy of our proposed routing protocol CORFA, we have considered both geographical and topological routing protocols and selected significant routing protocols from literature for performance evaluation. They are impactful in terms of their selected routing metrics and approach for VANET environment.

1. Performance Evaluation with Geographic Routing Protocols

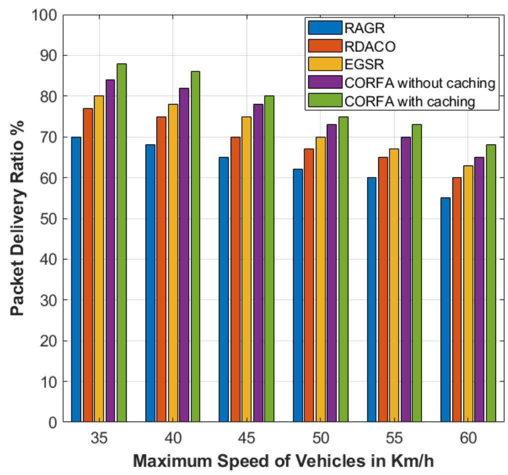
RAGR [56] depends on different routing metrics that are distance, direction and traffic density for data forwarding. RDACO [58] depends on ant colony optimization to discover all possible routes for data transmission. ACO ensures link quality of connected links. EGSR [61] is another protocol that uses ACO to compare link connectivity of the streets. This mechanism can handle road and traffic condition irrespective of the node mobility. All the aforementioned protocols provide efficient QoS under VANET environment.

i. Analysis of PDR Performance

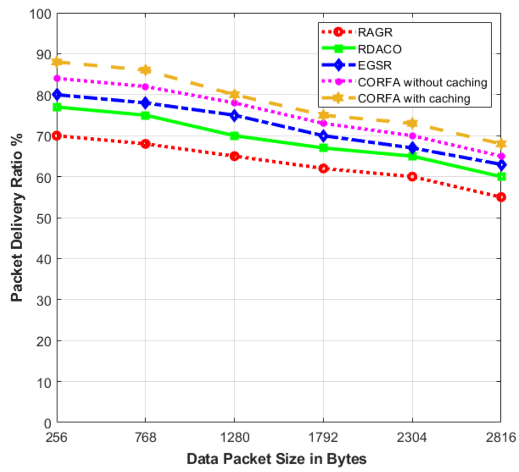
Figure 4.18 shows PDR comparison for RAGR, RDACO, and EGSR and proposed CORFA with respect to varying vehicular speed, data packet size, source to destination distance and vehicular density. Figure 4.18 (a) depicts that overall PDR performance decreases when vehicular speed increases. As RAGR selects roads on basis of distance, direction and vehicular density it is not efficient enough in packer forwarding. RDACO requires more forward ant packets for route discovery and backward ant packets for stable route finding. Whereas EGSR gives better result due to less broadcast of control packets. Although it follows ACO but still avoids backward route maintenance approach. CORFA generates less control packets and generates alternative path for link breakage, which results in better packet transmission. When caching is applied, it outperforms more because it eliminates route discovery process and initiates successful data transmission. Figure 4.18 (b) depicts larger data packet size affects

PDR performance. Packet size varies from 256 bytes to 2816 bytes. This happens due to increase in packet collision probability and fading. Figure 4.18 (c) shows source to destination distance variations from 1000m to 2000m. When S-D distance is less PDR performance is better. When distance increases, RAGR strives for packet forwarder. RDACO suffers from link breakage when distance increases due to its high route maintenance cost. EGSR outperforms from RAGR and RDACO as it has clear idea about its neighbor list. They uses digital map of the place and computes optimal path for destination. EGSR underperforms from CORFA as later one does not depend on single stable route it creates alternate data forwarders that can mitigate link failure scenario. Figure 4.18 (d) shows PDR performance comparison for varying traffic densities with constant vehicular speed of 50km/h. RAGR cannot perform well when traffic density metric is considered. RDACO suffers from broadcast storm; due to huge number of forward ant packets are broadcasted which degrades PDR performance. EGSR provides better result than RDACO because of its reduced ant packet broadcasting. CORFA uses RSU cache memory for data transmission. When congestion increases packet collision probability route discovery is not required and successful packet delivery is ensured.

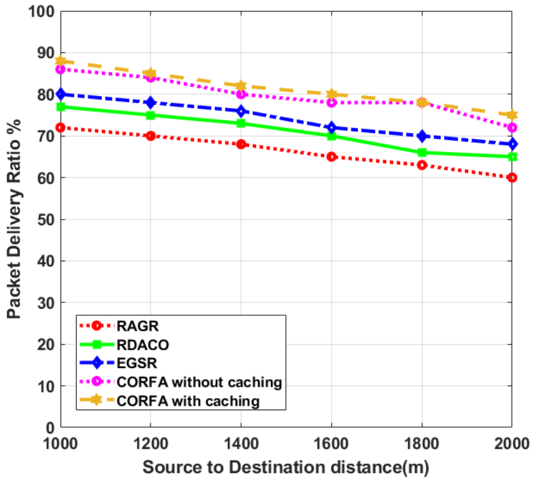
Table 4.6 is the Percentage Improvement of PDR with respect to Source to Destination Distance, Packet Size, Vehicle Speed and Number of Vehicles.



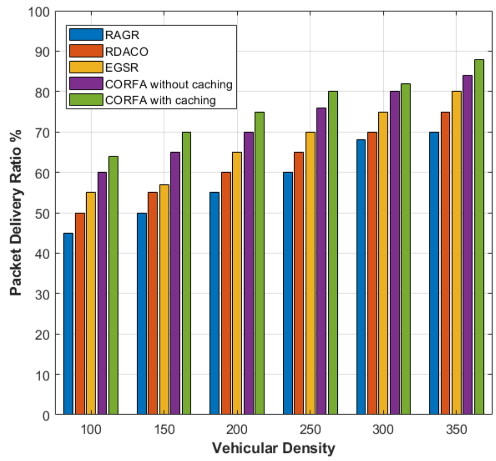
(a)



(b)



(c)



(d)

Figure 4.18: Packet Delivery Ratio Comparison with respect to varying (a) vehicular Speed (b) Data Packet Size (c) Source to Destination Distance (d) Vehicular Density

Table 4.6: Percentage comparison for PDR

Percentage Improvement of CORFA over RAGR, RDACO and EGSR				**Remark**
Metrics	**RAGR**	**RDAO**	**EGSR**	Better PDR performance is achieved for CORFA w.r.t all three others
Source to Destination distance	24%	15%	11%	
Packet Size	23%	12%	7%	
Vehicle Speed	27%	17%	13%	
Number of Vehicles	32%	22%	14%	

ii. Analysis of Network Latency Performance

Figure 4.19 shows network latency comparison for RAGR, RDACO, EGSR and proposed CORFA with respect to varying vehicular speed, data packet size, source to destination distance and vehicular density. Highest delay occurs in case of RAGR due to its selection criteria of routing metrics. Distance, direction and traffic density based road formation delays data packet forwarding. RDACO faces more delay because it takes time to complete route discovery and stable route formation through forward and backward ants. This scenario delays data packet transmission. EGSR takes longer time for finding the connected path from source to destination. In Figure 4.19 (c) for EGSR when vehicular speed increases delay increases more due to loss of connectivity. In case of CORFA there is route selection from destination to source which is not present in EGSR still it produces lesser delay due to its less packet retransmission and reliability. CORFA provides successful packets transmission in case of link breakage through alternate route without any delay. When caching is applied, it performs even better as there is less route discovery. The processing delay and propagation delay is negligible for longer paths.

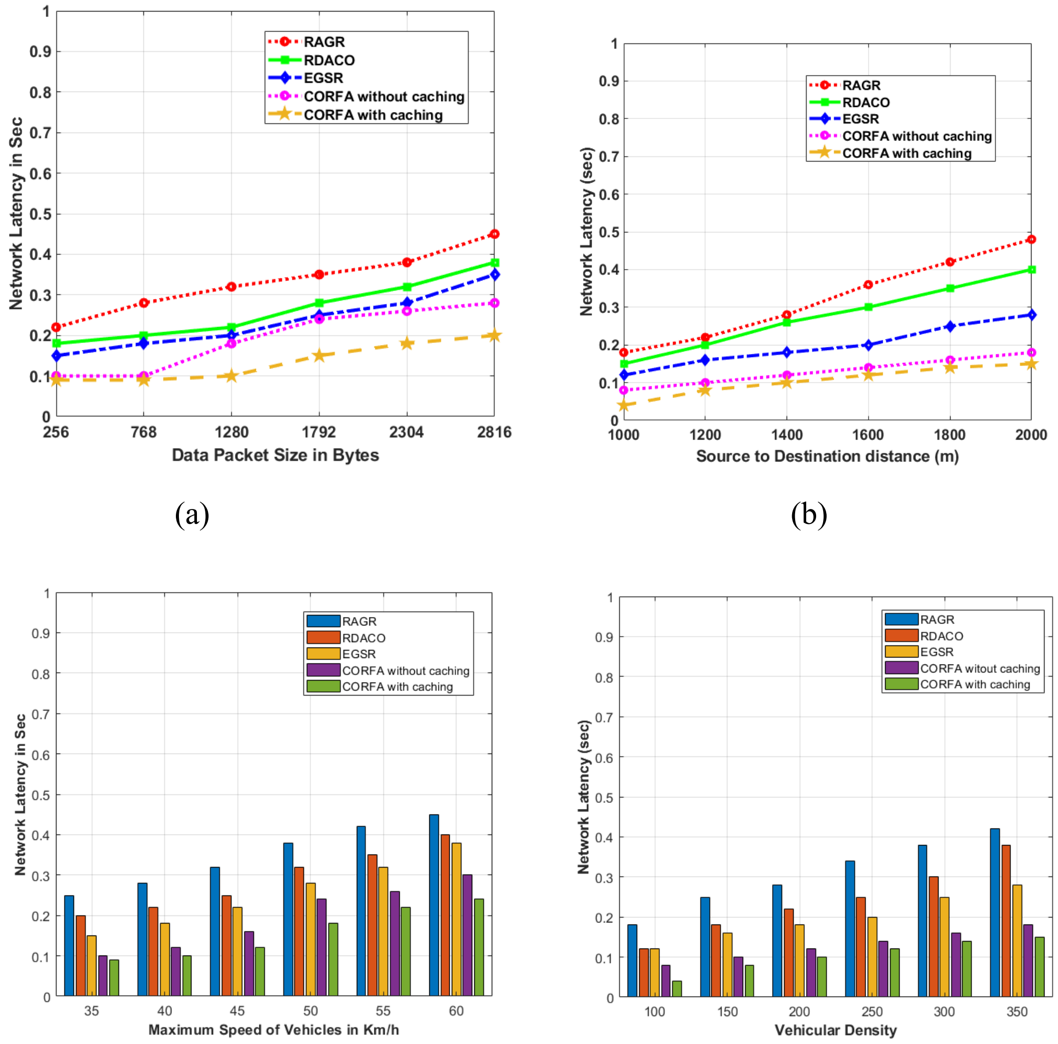


Figure 4.19: Network Latency Comparison with respect to varying (a) Data Packet Size (b) Source to Destination Distance (c) vehicular Speed (d) Vehicular Density

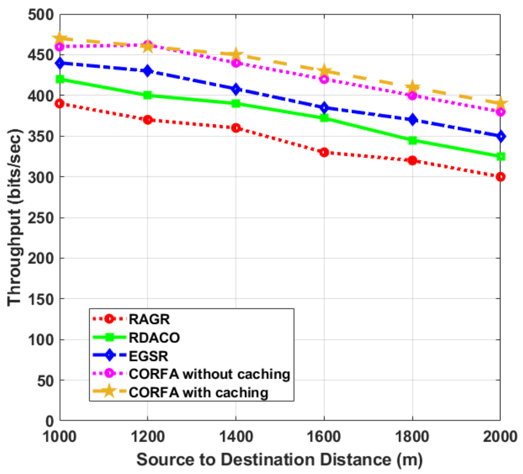
Table 4.7: Percentage comparison for network delay

Percentage Improvement of CORFA over RAGR, RDACO and EGSR				**Remark**
Metrics	RAGR (%)	RDACO (%)	EGSR (%)	Network Delay is reduced for CORFA
Source to Destination distance	-59%	-51%	-31%	
Packet Size	-59.83	-53.66	-17.83	
Vehicle Speed	-44%	-30%	-27%	
Number of Vehicles	-58	-45%	-29.66	

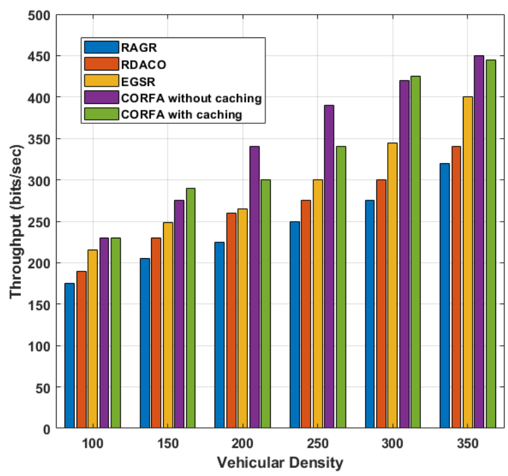
Table 4.7 shows the percentage improvement in latency with respect to Source-to-Destination Distance, Packet Size, Vehicle Speed, and Number of Vehicles.

iii. Analysis of Throughput Performance

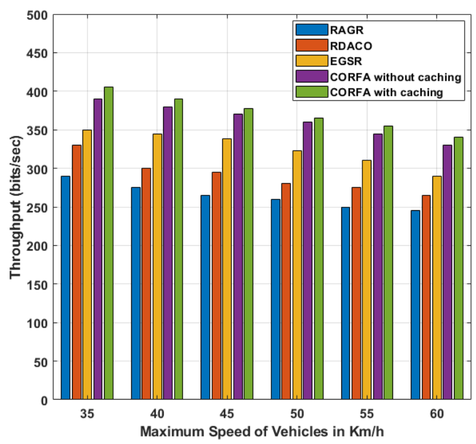
Next QoS parameter is throughput that is analyzed in Figure 4.20 with respect to (a) vehicular density (b) maximum vehicular speed (c) source to destination distance and (d) data packet size. Throughput increases with less packet drop and successful packet transmission. In case of RAGR, path is not determined before data transmission; this makes it unreliable and prone to packet loss.



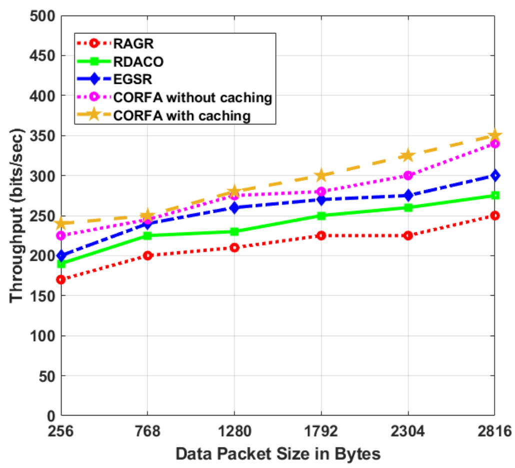
(a)



(b)



(c)



(d)

Figure 4.20: Throughput Comparison with respect to varying (a) Source to Destination Distance (b) Vehicular Density (c) vehicular Speed (d) Data Packet Size

In RDACO stable route is formed for control packets but for longer data packets it did not perform well. At the time of data packet transmission packet drop happens which reduces its throughput. EGSR gives better throughput than the prior ones; it even gives constant performance for the scenario changes. As it considers network connectivity and accordingly sets up edge weight, which reduces packet drop. Our proposed approach CORFA outperforms EGSR as throughput increases. There is less packet drop for utilizing alternate route and packet collision probability as control packet broadcast is restricted.

Table 4.8: Percentage improvement for throughput

Percentage Improvement of CORFA over RAGR, RDACO and EGSR				**Remark**
Metrics	RAGR	RDACO	EGSR	Throughput is increased for CORFA
Source to Destination distance	22%	12%	7%	
Packet Size	34%	20%	13%	
Vehicle Speed	38%	23%	12%	
Number of Vehicles	41%	23%	13%	

Table 4.8 shows the percentage improvement of throughput for CORFA algorithm with respect to Source to Destination Distance, Packet Size, Vehicle Speed and Number of Vehicles.

iv. Analysis of Routing Overhead Performance

Finally, the QoS parameter for routing overhead is depicted in Figure 4.21 with respect to (a) vehicular density (b) maximum vehicular speed (c) source to destination distance and (d) data packet size. RDACO sets up route through forward and backward ants and the same route is traversed twice for route discovery and route maintenance; this increases routing overhead and makes the performance worst among all. It underperforms than RAGR due to more control packets required for data packet transmission. RAGR evaluates direction and traffic density for the selection of next forwarder vehicle. As routing path is not reliable enough packet retransmission increases routing overhead. EGSR uses ACO still produces lesser overhead because it evaluates road connectivity parameters rather than vehicles. If vehicular density increases and maximum speed varies still it is able to give constant performance. Proposed approach CORFA broadcasts minimal control packets. Whenever next hop vehicles received and broadcasted it, previous hop vehicle stops transmission. Junctions placed with RSUs store routing tables for a certain time window and this reduces routing overhead rapidly. If source have to transmit data packet to previously traversed destination it just follows the predefined route.

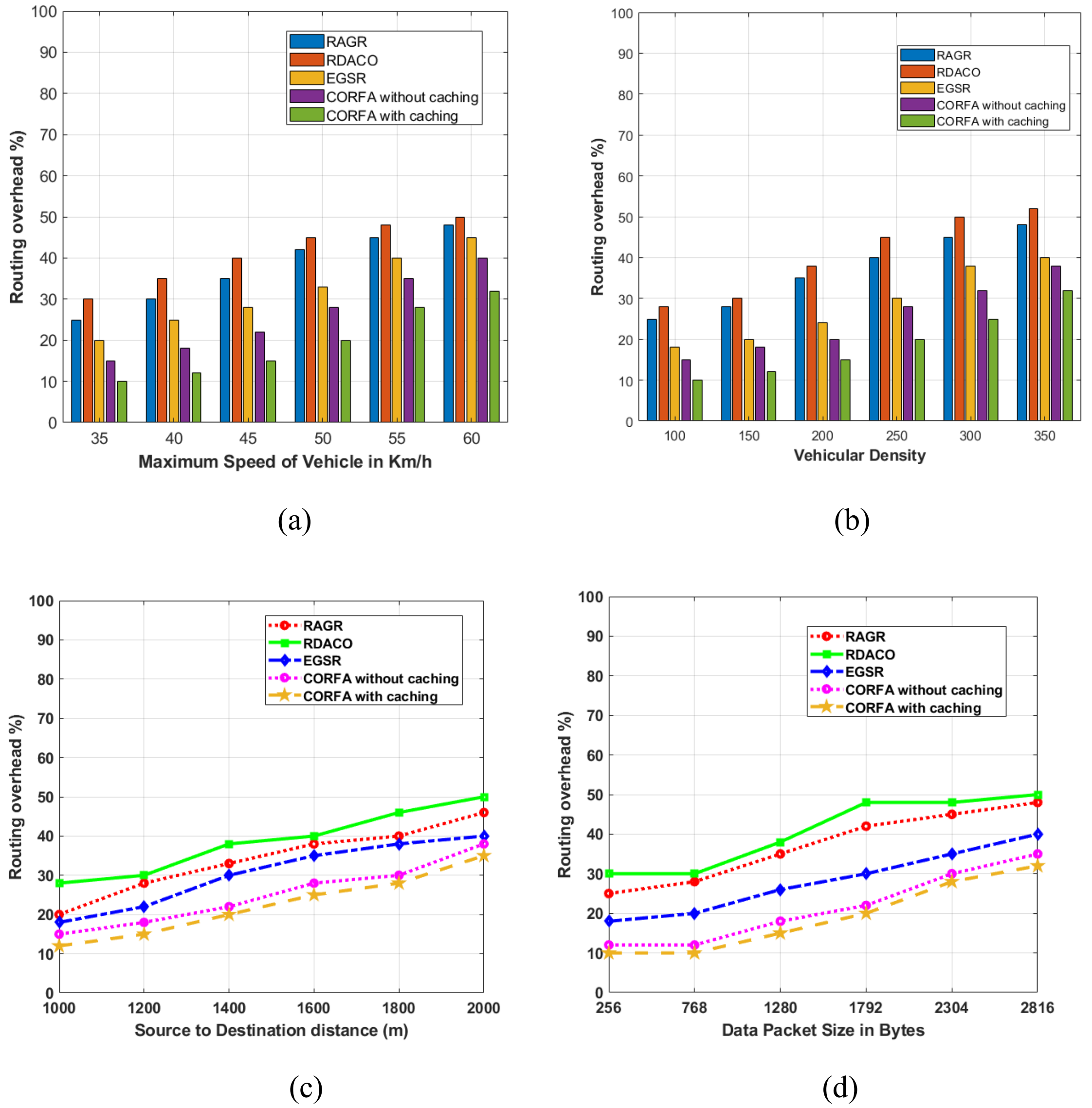


Figure 4.21 Routing overhead comparison with respect to varying (a) Vehicular Density (b) vehicular Speed (c) Source to Destination Distance (d) Data Packet Size

Table 4.9 gives the percentage improvement of Routing Overhead with respect to Source to Destination Distance, Packet Size, Vehicle Speed and Number of Vehicles.

Table 4.9: Percentage comparison for Routing Overhead

Percentage Improvement of CORFA over RAGR, RDACO and EGSR				**Remark**
Metrics	RAGR	RDACO	EGSR	Routing overhead is reduced for CORFA
Source to Destination distance	-29%	-38%	-21%	
Packet Size	-45%	-50%	-25%	
Vehicle Speed	-39%	-44%	-27%	
Number of Vehicles	-40%	-45%	-22%	

Furthermore, computation time with different traffic densities and varying number of hops is shown in Figure 4.22. It can be observed that the computation time increases when number of hop count and vehicular density increases. In case of proposed routing algorithm when number of hops increases computation time does not increase much because it is less affected by collision and packet drop. Our proposed routing algorithm outperforms in terms of computation time in comparison with the ACO based EGSR [61].

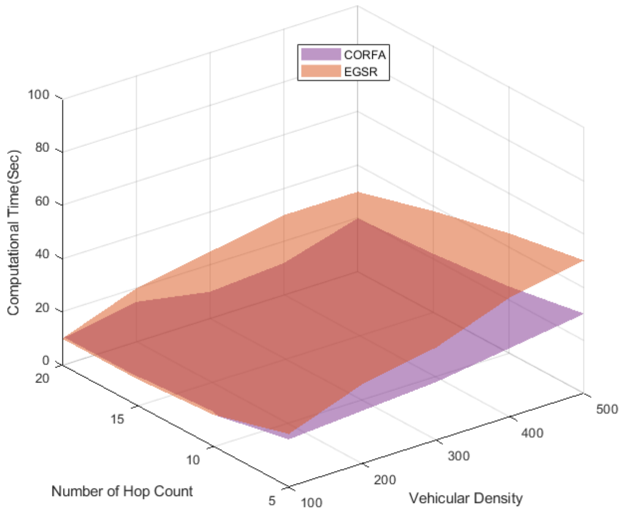


Figure 4.22 Computation time comparison with varying vehicular density and number of hops

1. Performance Evaluation of CORFA with topological routing protocols

Figure 4.23 illustrates QoS metrics comparison for OLSR, AOMDV, Ant AODV and proposed CORFA with respect to varying number of vehicles. We have considered both proactive routing protocol variant OLSR and reactive routing protocol variant AOMDV for evaluation purpose. ACO based Ant AODV is utilized to observe the effect of incorporating bio-inspired protocols in VANET environment. To begin with, the QoS metric PDR in 4.23 (a) it is observed that OLSR and AOMDV underperforms than bio-inspired protocols like Ant AODV and proposed CORFA. OLSR creates routing table through the periodic exchange of control packets irrespective of the requirement of route formation. This increases packet drop probability and degrades overall PDR performance. Unlike OLSR, AOMDV transmits route request packets to discover route whenever it is required. Source receives route reply messages from the present neighbour nodes in the network. As AOMDV creates multiple paths in one time route discovery, it performs better in VANET environment, which can handle link failure scenario efficiently and provides better PDR.

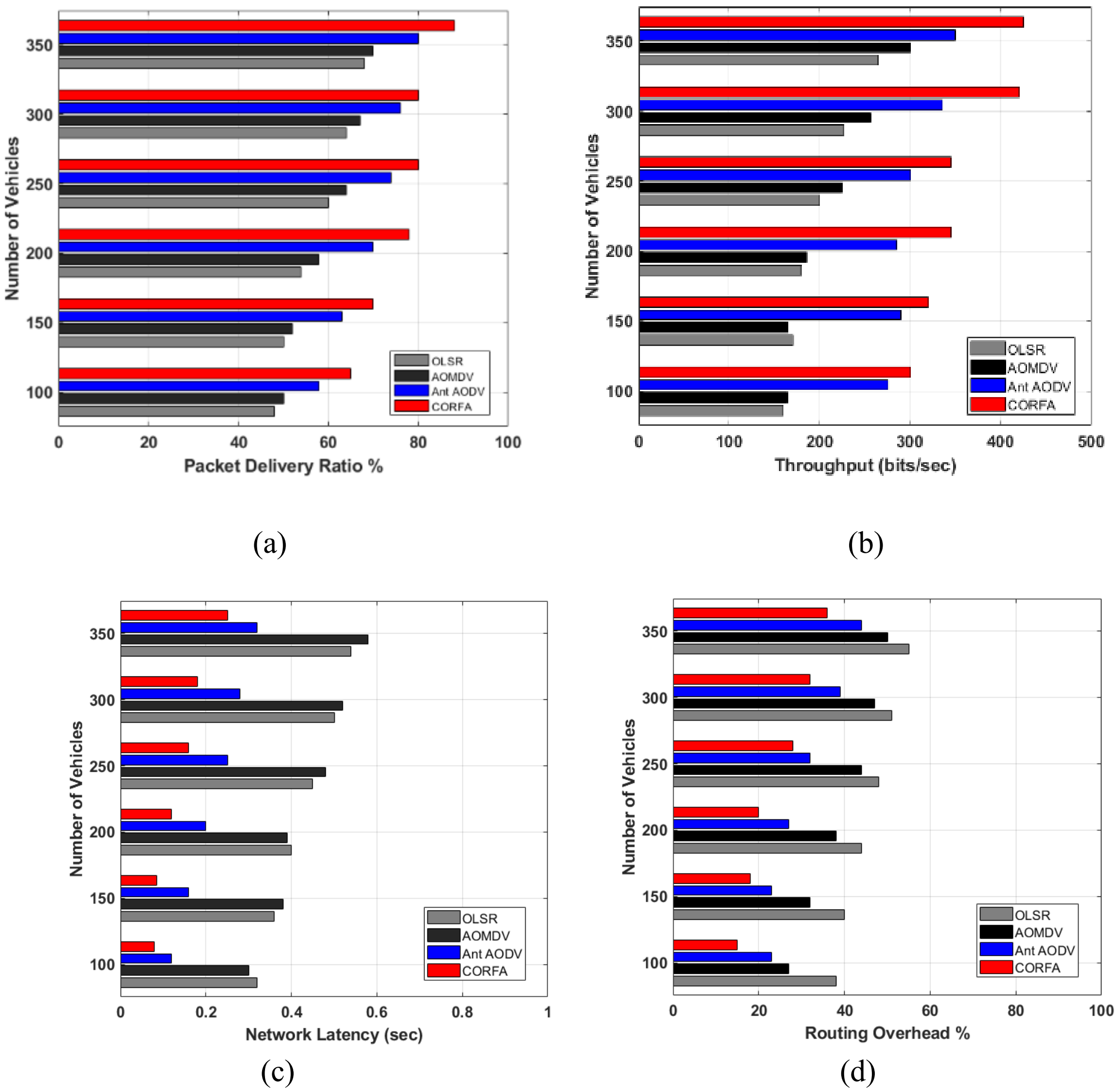


Figure 4.23 QoS comparison of CORFA with topological routing protocols with respect to varying vehicular density (a) packet delivery ratio (b) throughput (c) network latency (d) routing overhead

In Ant AODV, vehicles aware about the mobility information while route discovery process happens. As routes with minimal hop count with maximal link quality is discovered for packet transmission, PDR performance improves impressively. In our proposed approach, we have optimized route discovery process by less control packet transmission, which reduces packet collision. Alternate routes are created to handle link failure scenario. These factors directly affect PDR performance and able to provide best result among the comparison analysis.

Next considered metric is throughput, which is depicted in 4.23 (b). PDR and throughput are related and shown the same pattern in performance analysis. Although AOMDV gives marginal improvement than OLSR due to its on-demand approach and multiple route creation. Interesting observation can be visualized form the result that, when vehicular density is low packet collision is less for OLSR throughput is almost same as AMODV. When vehicular density increases in the network AOMDV outperforms OLSR because it initiates route discovery at the time of requirement only and handles link breakage because of multiple path availability. Although its route discovery process is flooded with route requests that affects throughput. Ant AODV discovers optimal path for packet transmission, which reduces packet collision and increases throughput than traditional topology-based routing algorithms. Our proposed CORFA optimizes route discovery process, which uses bandwidth efficiently and minimizes packet retransmission. Previously discovered route cached in roadside infrastructure which eliminates route discovery and maintenance in a great extent that reflects in enhanced throughput performance.

VANET is a delay-sensitive network that requires fast packet transmission. In Figure 4.23 (c) network latency, measured end-to-end delay for source to destination packet transmission is compared with varying vehicular density. Both OLSR and AOMDV produces more delay, which makes them less probable for VANET environment. OLSR suffers packet collision and retransmission in rapid vehicular network, which increases delay. AOMDV establishes path for packet transmission through route-request and route-reply mechanisms, which introduces delay in packet forwarding. On the contrary, ant AODV and proposed CORFA follows optimal route discovery process. Ant AODV secures less delay as it accounts minimal hop count to select best route, which ensures efficient packet transmission. Our proposed CORFA uses roadside infrastructure intelligently to cache already discovered routes that reduces delay occurrence for route discovery. It also manages link failure and packet retransmission delay with the help of alternate routes. Final comparison metrics is routing overhead percentage that shows in figure 4.23 (d). OLSR broadcasts link status periodically to neighbour nodes this enhances network overhead. AOMDV follows route request, route reply and route maintenance mechanisms according to requirement, which initiates routing overhead. Still, it gives better performance than OLSR as it creates multiple routes that are capable of handling link failure situation. Ant AODV and proposed CORFA produces less overhead in network. In ant AODV stable route is found based on link quality and hop count parameter. It is modelled according to VANET environment so that path with high signal strength used for data transmission. This results in low bit error rate and less routing overhead. Our proposed CORFA utilizes best route and subsequently creates alternate routes for packet transmission. It avoids route discovery when route is available in roadside infrastructure, which reduces routing overhead in a great extent.

Table 4.10: Performance comparison of CORFA with topological routing protocols

Percentage Improvement of CORFA over OLSR, AOMDV and ACO-AODV with varying vehicular density				**Remark**
QoS Metrics	OLSR	AOMDV	ACO-AODV	PDR and Throughput is increased Overhead and delay is reduced
PDR	34%	27%	9%	
Delay	-66%	-68%	-38%	
Throughput	79%	66%	17%	
Routing Overhead	-46%	-37%	-20%	

2. *Convergence Analysis with Bio-inspired VANET routing Protocols*

In this section comparison analysis is conducted to observe the efficiency of CORFA. Figure 4.24 shows the convergence analysis for the proposed CORFA, CSO-GR and PSOR. We have selected the bio-inspired algorithms with available fitness function for VANET routing from the literature. Fitness function is derived to identify best fittest neighbor for packet forwarding. It is clearly visible that CORFA reaches to the stable value much earlier than PSOR [64] and CSO-GR [67]. As we have used minimizing function so the smaller the fitness function value is, the more it is in favour of the routing requirements. Time complexity of CORFA is calculated by counting the loops in the algorithm. If there are n number of vehicle and m number of messages exchanged then the complexity of CORFA becomes $O(m \times n)$.

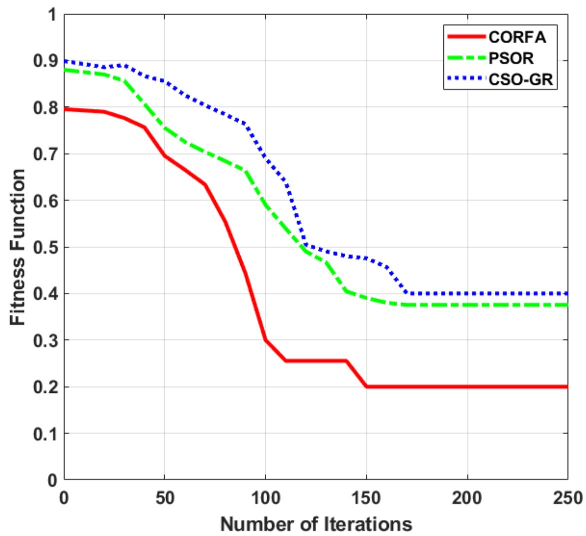


Figure 4.24 Fitness function comparison of CORFA with PSOR and CSO-GR

4.4 Chapter Summary

The research contributes in this chapter ensures QoS enhancement by proposing VANET routing algorithms namely RRO-ACO and CORFA. In case of RRO-ACO the vehicles deposit pheromone in their communication path to provide an idea about the feasible path for next hop vehicles. Whenever vehicle receives data, it immediately broadcasts acknowledgement with data packet so that less suitable routes stop data forwarding. This algorithm suits well for dense roadways as well as sparse highways where traffic is significantly low as evident from the results depicted in Table 4.2. RSU takes part when next hop vehicles are out of coverage area, which increases stability and reliability. Simulation explores that RRO-ACO performs better in terms of packet delivery ratio, throughput and network latency.

As ACO optimization, based algorithms have the limitation of recurrent route discovery that enhances network overhead, in our next phase of research in this chapter concentrates towards the further modification of routing algorithms. A VANET routing protocol named as CORFA is proposed for packet transmission in urban environment. In CORFA, by employing small control packets, called barking packet, vehicles determine the next forwarder on the basis of link stability and successful packet transmission probability of the paths. Control packets are broadcasted by such a planned manner that restricts the occurrence of broadcast storm situation. This protocol utilizes the presence of RSUs to decrease the burden of route discovery and delivers pre discovered routes in a convenient way. RSU storage is used to cache vehicle route tables for a certain time limit. Simulation results conclude that proposed CORFA outperforms than both geographical and topological routing protocols RAGR, RDACO, EGSR and OLSR, AMDV, ACO-AODV in terms of PDR, delay, throughput and routing overhead. Detailed comparison for each parameter with respect to varying traffic density, source to destination distance, packet size and vehicular speed are observed and given the comparison tables. CORFA is evaluated and validated its superiority for both the mode of operation where caching is applied and vice versa. This ensures that this protocol is not solely depends on the infrastructures like RSUs at every intersection keeping in mind the huge RSU installation cost. This approach is more suitable for city traffic scenarios where sufficient number of vehicles are always present on road.

❖ Publications from this chapter

1. Sreya Ghosh, Iti Saha Misra, Tamal Chakraborty, "Improved Quality of Service by canine olfactory route finding algorithm for Vehicular Ad Hoc Network. Transactions on Emerging Telecommunications Technologies. 2023 Jun; 34(6): e4764.
2. Sreya Ghosh, Iti Saha Misra, "Enhanced QoS Performance with Reduced Route Overhead by Ant Colony Optimization Algorithm for VANET", In 2020 IEEE Applied Signal Processing Conference (ASPCON) 2020 Oct 7 (pp. 237-241). IEEE.

5

Congestion Mitigation and Emergency Path Planning for Smart City Design

5. Congestion Mitigation and Emergency Path Planning for Smart City Design

Outline of the Chapter:

5.1 Introduction

"The most precious resource we all have is time." — Steve Jobs

It is evident from the preceding chapters that ITS can facilitate smooth, faster, and safer transport by attenuating some of the prime concerns such as congestion, traffic pollution, and accidents arising due to rapid urbanization. Chapter 3 has put down the essential efforts for the implementation of optimal roadside infrastructure deployment using ITS. To introduce ITS for the development of smart city design and truly take benefits of ITS, the first step should be the exploration of enormous application areas using vehicular networks consisting of RSUs, traffic sensors and cloud servers.

One of the preliminary objectives of any efficient transportation system is timeliness, which is severely affected by traffic jams and unorganized route planning. Therefore, careful concentration must be given towards reduction of travel time and reaching to destination as early as possible. Accordingly, one of the contributions of this Chapter is to build a variable speed limit (VSL) system to prevent congestion due to uncontrolled gathering of vehicles at junctions. In the next phase of contributory work, a recommendation system is designed to suggest appropriate healthcare destination in emergencies and provide a convenient route for reaching there immediately.

India, with its accelerating growth towards urbanization, is experiencing a tangible boost in the number of vehicles circulating on roads. The urban transport system becomes inefficient and fails to meet its capacity index, which adversely affects the economy and quality of life [166]. Implementing ITS in association with Wireless Sensor Networks and IoT (Internet-of-things) paradigms optimizes road capacity in terms of traffic and road geometrics [167].

Managing traffic in Indian metropolitan cities is a herculean task due to its highly heterogeneous nature. Few projects that cater to notable progress are the Advanced Traffic Management system in Chennai named Traffic Regulatory Management System, Area Traffic Control in Mumbai, Vehicle tracking, Electronic Toll Collection in Bangalore and Hyderabad, etc. [168]. Kolkata still struggles to cope up with its colonial structure and ever- increasing number of traffic [169].

Besides GPS based proactive approach it is necessary to deploy a centralized and connected road network with both fixed and ad hoc infrastructure to address root cause of congestion. A smart ITS solution needs adaptive, cooperative and dynamic Vehicle to Vehicle (V2V), vehicle to Road side unit (RSU) and RSU to backhaul communication backed by sensors, detectors [170]. Indian roads are prone to congestion due to static speed limit systems. Its reliability is poor because of its unrealistic traffic management. If the speed limit is 60 km/hr for a particular roadway and severe congestion occurs then there is no other way rather than stuck in a jam and a desirable speed limit is never achievable. On the contrary, when the road is empty drivers should follow the speed limit but they tend to exceed that which increases accident risks. A variable speed limit (VSL) system should be implemented to display appropriate speed based on the real-time situation. VSL systems improve road safety as well as reduce the congestion time. Keeping in mind the major objective of this chapter, we propose a RSU controlled speed-limiting system that reduces travel time.

Travel time reduction is not only advantageous for transportation sector but the incorporation of ITS applications can be very much advantageous for healthcare systems also [171]. Therefore, in the next phase of this chapter, we have designed an effective application for healthcare. One of the major hazards faced by patients and their relatives is to find out appropriate healthcare destination in an emergency. Plenty amount of data is available in Internet and in emergency; it is quite difficult to arrange them and make a quick decision [172]. Especially in developing countries like India, at the time of the pandemic it is difficult to manage huge medical costs and their shortage. This motivates us to develop a recommendation system framework that not only explores the closest healthcare destination but also considers patients' demands.

In practical life decision-making, biological systems provide a favourable framework for problem resolution such as the firefly algorithm [173], ant colony optimization [174], and many more [175], [176]. Their self-adaptation feature means looking forward to new suitable paths when the destination changes; making them appropriate choices for route finding in the dynamic urban environment.

Google maps provide shortest route for a fixed destination. When destination is unknown and depends on some prerequisites, a recommendation system is required. Consequently, an application is implemented that can assist users to select most suitable hospital and its optimal navigation. For route recommendation, this scheme can receive road traffic information from RSU that is an integral part of VANET.

5.1.1 Contributions of this chapter

The primary contributions of this chapter are summarized below.

- The proposed VSL system is designed to promote smooth and fast vehicular movements through the roadways by intelligent handling of intersections.
- In this work through a simulation analysis, we have performed travel time and speed comparison for controlled and uncontrolled scenario.
- Furthermore, we also design and implement an ITS application for arriving at appropriate healthcare destination which saves time at emergency. This work has two phases where the first one is multi criteria decision making (MCDM); creation of a Web API for that and the second one is to find out the shortest path.
- For MCDM, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is used and optimal path is decided by nature inspired firefly algorithm.
- For performance analysis, traffic simulation is implemented in SUMO and travel time is estimated for congested, moderate and normal traffic densities. Lastly, Firefly algorithm is compared with Dijkstra algorithm for travel time and computational time.

5.1.2 Chapter Organization

The chapter is structured as follows. In section 5.2, the proposed VSL system is outlined which includes its system model in subsection 5.2.1 along with the results analysis in subsection 5.2.2. Thereafter, section 5.3 demonstrates the design and implementation of the ITS application for emergency healthcare destination finding. While system model and performance evaluation is described in subsection 5.3.1 and 5.3.2 respectively. Lastly, we conclude the chapter in section 5.4.

5.2 Controlled Speed Limiting System

Intelligent transport system is the new aspect of smart city design under the purview of digital India. Conventional approaches like rerouting from congested paths, predictive control methods are impractical for Indian scenarios due to excessive growth of urbanization, unorganized and heterogeneous traffic nature. A novel framework is required to ensure smooth traffic, less congestion and avoiding accidents. This research contributes towards the ITS that provides a controlled speed limit to the cluster of vehicles according to present roadside conditions. Smart RSUs (Road Side Unit) are responsible for analyzing and controlling the road network. Several traffic metrics like travel time, vehicle speed and the effect of signal spacing on vehicular speed are analyzed with the designed system model and have compared them with the conventional uncontrolled scenario. This work is mainly focused on Kolkata, the newbie smart city of India. It is observed that with the proposed design model for ITS, significant improvement of vehicle movement is achieved in a very congested hour avoiding stagnant conditions more often we face in Kolkata.

5.2.1 System Model

Flow chart description of our proposed model is given in Figure 5.1. This model uses smart RSU (Figure 5.2) acts as an integral part of comprehensive ITS uses the idea of the Internet of Things (IoT). RSU collects information using a variety of sensors and detectors and collected information is processed and used to adjust speed. Each intersection is deployed with a fixed RSU to decrease NLOS (Non-Line of Sight) transmissions along the road network to provide better coverage. RSU is linked with the base station through LAN (Local Area Network) gateway. Vehicles are equipped with an on-board unit (OBU) so that it can communicate with other vehicles and RSU. OBUs periodically send a beacon packet to neighbouring RSU. The packet format includes speed, ID, vehicle’s current position. RSU acts as a smart unit with computing and networking capabilities processes this data after a periodic interval of time along with the total number of vehicles throughout the road section and classifies the road status such as congested, moderately congested, etc. RSU-to-vehicle and vehicle-to-RSU communication follows the Dedicated Short-Range Communications (DSRC) spectrum which is based on the IEEE 802.11p standard at 5.9 GHz with allocated bandwidth of 75 MHz by the U.S. Federal Communication Commission specifically used for V2I and V2V communications [177]. A road segment with a single entry and exit point starting from point E in Figure 5.1 is divided into cells using the CTM (Cell transmission model) strategy developed by Lighthill, Whitham, and Richards based on the piecewise linear relationship between flow and density [178]. A small section of road can be governed in a much simpler way rather than the whole road length. As depicted in Figure 5.2, RSU1 recorded and broadcast vehicle density from built-in sensors. RSU2 broadcasts its permissible range of a particular traffic cycle and RSU1 controls speed for each segment in such a way that vehicles arrive at the next entry point more stably. RSU1 sets a controlled speed for a cluster of vehicles and sends it through V2I communication. Without the speed control, whenever a huge amount of traffic arrives in rush hour, it creates enormous delay due to the accumulation at junction points and rigorous capacity drop happens. To accommodate huge incoming traffic RSU2 increases the speed of outgoing vehicles within the maximum speed limit for the road i.e. free-flow speed.

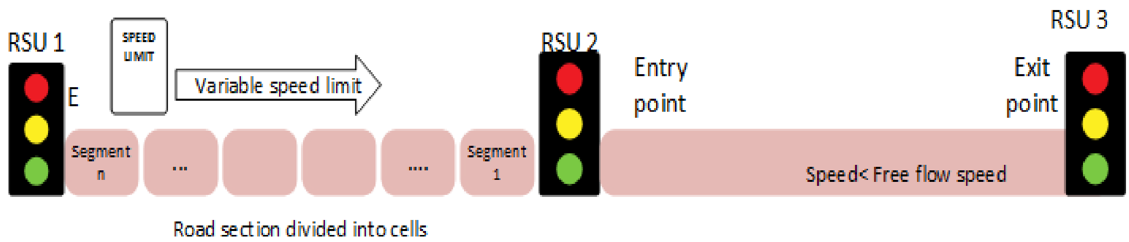


Figure 5.1 Schematic Model for Speed limit control

Determination of Speed of Vehicles

Let, Ni is coming at RSU1 and free flow road capacity will be, $f_i = \frac{w}{x_i+c}$.

Ni	$No\ of\ incoming\ cars$
f_i	$No\ of\ vehicles\ at\ free\ flow\ condition$
w	$road\ width$
x_i	$average\ car\ length\ at\ a$ single instance of time

So, three situations can arise here,

$N_i < f_i$ – means the number of incoming cars is lesser than the number of cars can go through.

$N_i = f_i$ –means the number of incoming cars and the number of cars can go through are equal. $N_i > f_i$ –means the number of incoming cars is greater than the number of cars that can go through. In a normal scenario, if $N_i =< 2. f_i$ then it is not an issue as, one batch of vehicles is going through, and another is waiting. However, the problem arises when $N_i \gg f_i$. As we know, N_i is a variable, so the solution needs to be dynamic to handle the number of incoming cars (N_i) so that the number of vehicles cannot arise over the permissible *(Pi)* range.

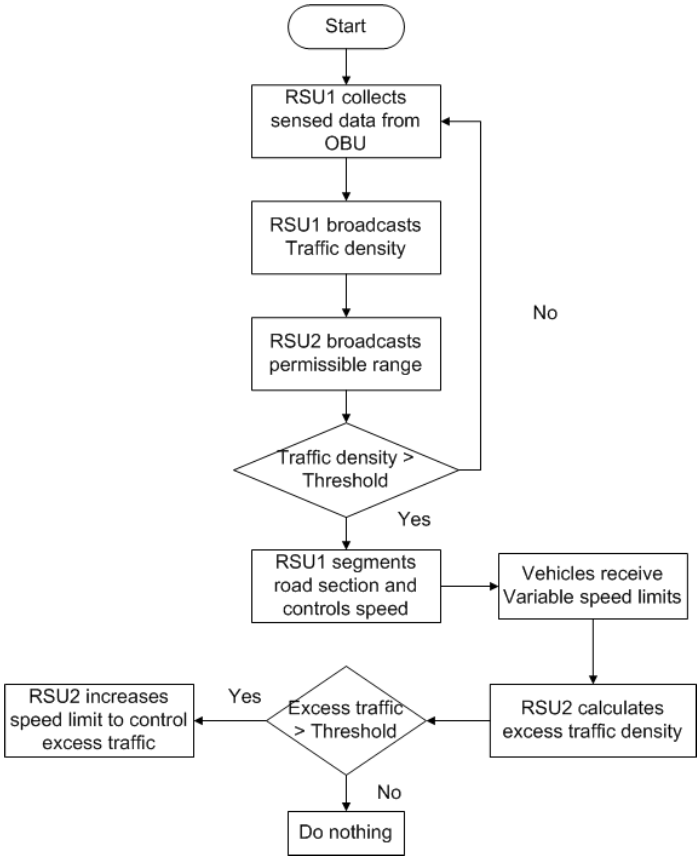


Figure 5.2: Flow chart of variable speed limit control

The road is segmented into X number of blocks $N_i = Xf_i$. The length of each block should be long enough so that vehicles will not pass two blocks within one-time interval. For each block, velocities are in harmonic progression. The velocity of the i^{th}vehicle of n^{th} cell is,

$$V_i = \frac{\int_0^{t_i} \frac{du_f}{dt}}{\sum t_i + (n-1)\sigma} \tag{5.1}$$

Where, the road length is an integral part of free-flow controlled speed (u_f) and t_i is the travel time in free-flow condition, n is the natural number and σ is the buffer time. As velocities are controlled for each vehicle in each cell, so the uniform acceleration is negligible for this scenario. From RSU2 to exit point velocity is less than free flow velocity u_f, which is denoted as the highest speed limit in the city.

The adapted macroscopic traffic model depicts traffic flow like a fluid based on classical and continuous LWR model. The aggregated and dynamic quantities that are involved to build up are denoted by average speed $v = v(t, l)$at location l and time t with traffic density $k = k(t, l)$, the number of vehicles arrive per unit length of the road and lastly the flux, which can be expressed by the fundamental relation $q = kv$. The continuity equation for conservation of flow over space and time will be [179],

$$\frac{\partial k}{\partial t} + \frac{\partial q(k)}{\partial x} = 0 \tag{5.2}$$

$$V(k) = V_{max}\left(1 - \frac{k}{k_{max}}\right) \tag{5.3}$$

where , V_{max} is maximum speed and k_{max} is maximum traffic density. Then the flow of traffic can be represented as,

$$q(k) = kV_{max}\left(1 - \frac{k}{k_{max}}\right) \tag{5.4}$$

To design real-world traffic in a nearly accurate way, we use Greenshield model that assumes a unique relation between speed and density [180].

For road path length (L), the maximum number of vehicles can be served is denoted by,

$$N_{max}^{L} = \ k(t, l) \times L = \sum_{all\ cells} \frac{q(k)}{v(t,l)} \times L \tag{5.5}$$

Determination of total travel time

If traffic density is low, the speed of the vehicle is close to free-flow model, otherwise, during traffic congestion, the speed of vehicles come to a complete stop. Speed is the exponentially decreasing function of density where free-flow speed is u_f, k is the traffic density and k_c is critical traffic density [168]. Density greater than critical value means traffic is in a congested state.

$$V = u_f exp(-\frac{1}{2}(\frac{k}{k_c}^2)) \tag{5.6}$$

In the congested state, the traffic time increases exponentially, so, for the present scenario where no speed limit control is applied, total travel time (T_{normal}) is given as,

$$\sum_{1}^{N_i} T_{normal} = \frac{L}{V} + t_{waiting}.I_i \tag{5.7}$$

Where $t_{waiting}$ is the normal traffic signal waiting time, and I_i is the number of the interval, the traffic signal has to be triggered.

Due to the uncontrolled speed of the vehicles and also a complex driving pattern of the drivers, the congestion control becomes more complex, and with the higher number of incoming vehicles, the speed becomes zero. This situation happens every year during the festive season in Kolkata, where more than an hour is needed to cover only 1 km distance. In our model, due to a controlled and intelligent speed- limiting system T_{cs} will be,

$$\sum_1^{N_i} T_{cs} = \frac{L}{u_f} + \frac{|(N_i - f_i)|}{f_i} . \sigma \tag{5.8}$$

Where , $N_i \geq f_i . \frac{L}{u_f}$ denotes the initial travel time under free-flow conditions.

5.2.2 Results and Discussions

The analytical model is formulated in MATLAB and evaluated in terms of traffic performance indices. This model is categorized and performed according to Kolkata centric traffic database. Kolkata has to face a humongous amount of traffic density whereas road space in Kolkata is only 6 percent compared to Mumbai and Delhi [181]. A high demand of mobility with low road space results in a high level of congestion in Kolkata. The car-density of Kolkata is just behind Mumbai, almost 319 per km, which is well addressed in our model. The maximum speed limit for our model is considered 40kmph [169]. Building up a traffic signal is a huge cost consuming task. Exact signal spacing is required to continue progressive traffic flow on urban roadways [182]. Kolkata traffic police have some rules to set up an intersection point [183]. In our model, we are taking an average roadway length of 1km according to [184].

Table 5.1: Traffic parameter used in the simulation

Parameters	**Default Values**
Road path Length (m)	1000
Average Vehicle length (m)	5
Buffer time (s)	5
Free flow Speed (km/h)	45
Inter vehicular Gap (m)	2

Buffer time is the intercellular time. Normally a driver takes an average of 7m/s^2 to stop the vehicles and reaction time of 1.5 to 2 seconds [185]. So an average of 3 seconds is needed.

Therefore, buffer time includes driver's response time and the RSU Processing time, 2 seconds, which include sensing the road, processing, and communication over IEEE 802.11p.

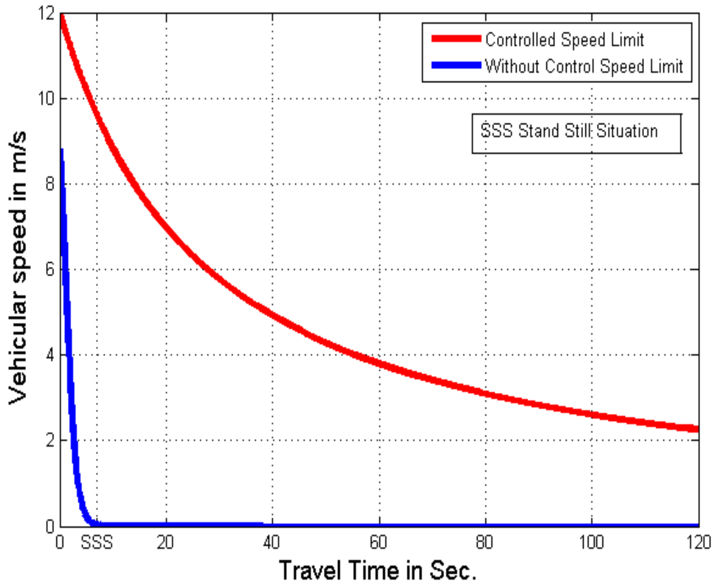


Figure 5.3 Comparison of Time vs. speed limit of our proposed model with uncontrolled speed

The average maximum speed limit of Kolkata is around 40km/h (11.1 m/Sec). As observed from Figure 5.3, speed is decreasing much faster without the speed limit control where in case of speed control it is reducing much slower as a result stagnant situation over a long period may be avoided. In case of no speed limit control stand still situation occurs much earlier. In actual Kolkata city scenarios, road path length (distance between entry-exit point) is not uniform, in many places, it is greater or less than 1 km. Inside the city, junction points are closer than highways. That scenario is depicted in Figure 5.4 where path length varies from 500m to 3000m for our controlled speed limit model. Larger the entry-exit point distance, lesser unnecessary stoppages, and road intersections vehicles have to face, which causes vehicles to slow down. Due to this, our model also performs well when length increases. In a normal scenario, in the national highways, the speed is much greater than the speed inside the city. Lesser number of junction points will increase the overall speed limit.

Further, the inter-cell waiting time or buffer time varies up to 30 sec. In the normal scenario, the buffer time includes the waiting time, may increase heavily, due to some catastrophic event, or during Durga Puja time. In Figure 5.5 it is clearly observed when buffer time (σ) is increasing, automatically travel time is also increasing with the same number of vehicles. This indicated that for a particular traffic density within a sector under RSU, buffer time needs to be set to optimize the travel time within this road segment.

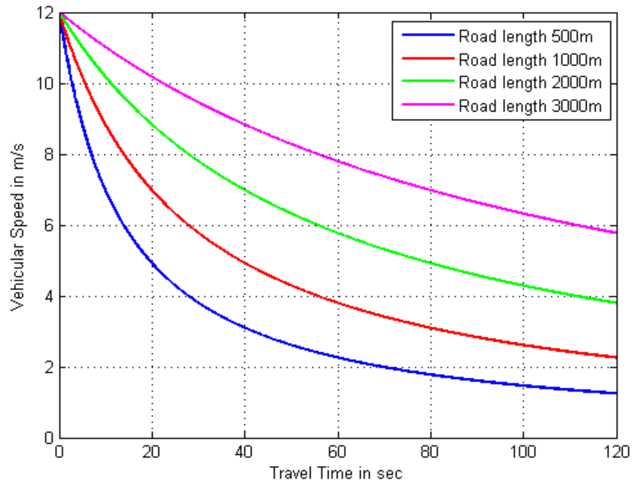


Figure 5.4 Comparison of Time vs. speed limit for different path lengths in case of controlled (variable) speed limit

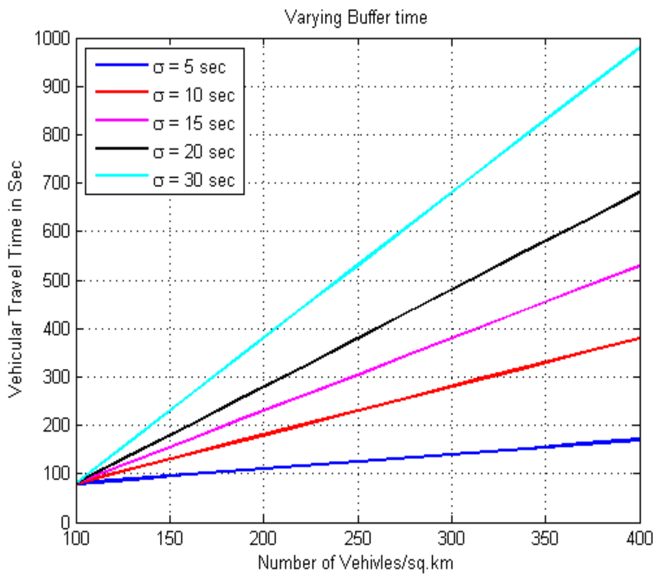


Figure 5.5 Comparison of Number of vehicles with Travel time for increasing buffer times for our controlled speed limit model

In Figure 5.6 we plot the outcome from the proposed traffic model by considering traffic statistics of Kolkata as an instance. Kolkata faced an average vehicular density of 319 vehicles/km [186]. It is observed that our proposed model outperforms in comparison with no speed control approach above a certain traffic limit (227 vehicles/km) i.e. with heavy traffic conditions reducing total travel time. It makes sense as within a certain road space there will be always a limit for the maximum number of vehicles to be allowed for a certain buffer time and road length which the proposed VSL method provides. Controlling this way in every road segment will ultimately give a smooth traffic flow within the city area with a reduced chance of road accidents. When traffic density is low and there is no control of the speed limit it performs better than our proposed control model as an obvious reason. For any congested city like Kolkata, when density increases, our proposed method will perform well as we see from Fig. 6 that when the traffic numbers exceed 319 cars/km VSL provide still controlled flow. Travel time is much lower for higher densities validating the reason for which we propose this method for ITS.

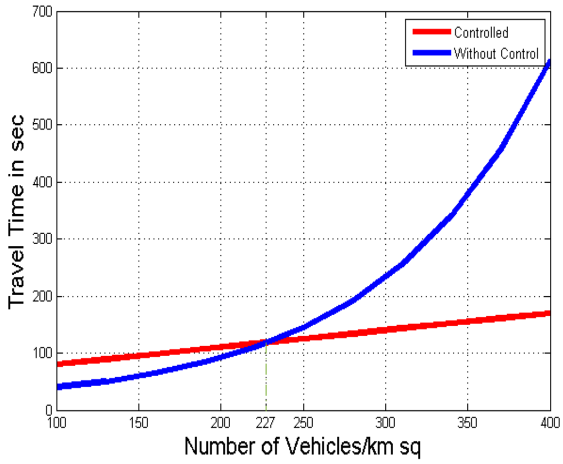


Figure 5.6 Comparison of Number of Vehicles vs. Travel Time
(In both the cases Road Length =1000m and σ = 5sec for controlled model)

5.3 Emergency healthcare application based on ITS

Intelligent Transportation Systems have become the emerging thrust area of research because of their enormous applicability in day-to-day life. In an emergency reaching to the appropriate hospital/health care center as early as possible can be lifesaving. In this chapter, a hospital recommendation system is proposed that reviews different criteria like expenditure, healthcare provisions, etc., and generates proper direction to reach there. A multi-criteria decision-making algorithm TOPSIS is used to determine hospital ranking according to the comparison matrices. A real-time database has been created in the Amazon web service (AWS) server that contains hospital locations, bed availability, etc. A web application has also been made where user can visualize the hospital name, location, and path. Route suggestion applies meta-heuristic firefly approach where the destination can be altered if the surrounding conditions change.

5.3.1 System Model

Figure 5.7 describes communication architecture. Smart phones are connected through cellular networks or Wi-Fi access points. Vehicle to Infrastructure communication acts in accordance with 802.11p DSRC protocol [187]. The server is connected through an internet backbone with a heterogeneous VANET wireless framework. In Figure 5.8, basic schematic diagram of the proposed recommendation system is depicted. The real-time database that contains hospital information has been made in AWS (Amazon Web Services) dynamoDB [188]. An exclusive platform is used to formulate a database for web development purposes. The user sends their location and status in the web application and receives the recommended hospitals' whereabouts. Real-time database contains hospital names, location, bed, ICU availability, and last but not the least budget at a certain time. The path-finding mechanism to the destined health centre follows the firefly algorithm. This algorithm suggests a feasible route to the destination. Figure 5.8 is the schematic diagram of the proposed system model.

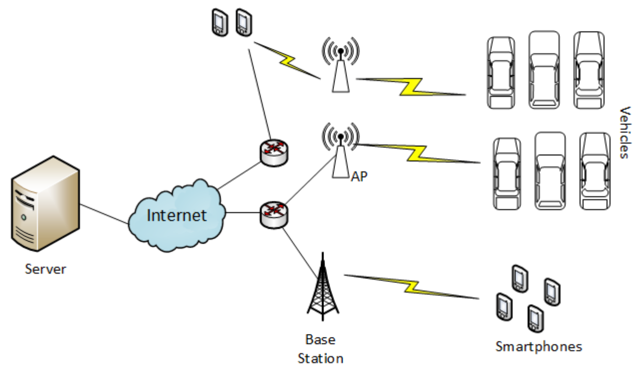


Figure 5.7 Communication Architecture

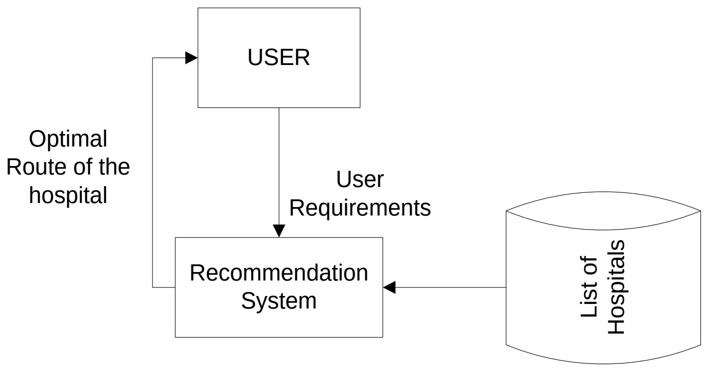


Figure 5.8 Schematic of Proposed Recommendation System

System functional flow diagram is represented in Figure 5.9. User inaugurates search and gives their updated medical condition to the Recommendation System server which is a component built under ITS. Real time database that is created by AWS for hospital information is being retrieved and enforced multi criteria based decision-making algorithm such as TOPSIS that determines the most suitable healthcare destination nearby. For emergency service, an optimal route to reach the destination hospital is a necessity. To serve the patient-carrying vehicle an optimal route guidance will be produced using Firefly algorithm in this work. The recommendation system periodically checks the most appropriate health care centre for the request received from a patient party. The system will also notify the best alternative to the patient party in between the trip to the earlier destination when the later one is the most suitable one. The stepwise flowchart explains the entire process of finding the health centre under emergency.

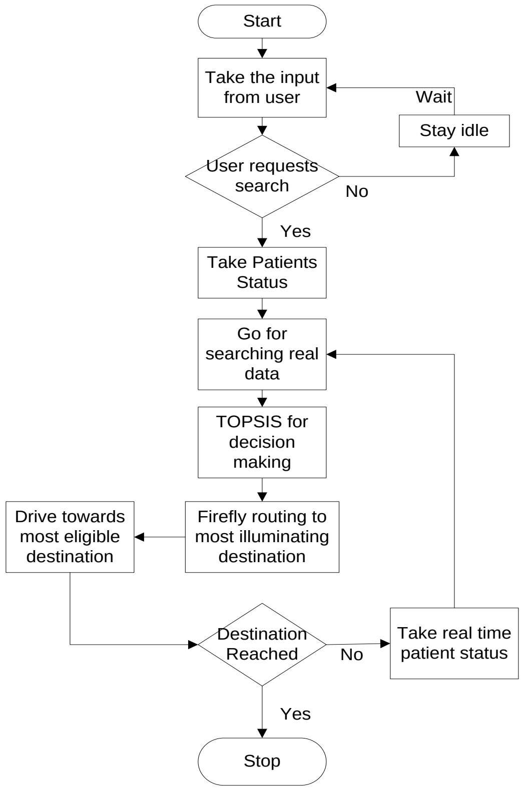


Figure 5.9: Functional Flow Chart for the proposed model

A. Using TOPSIS Algorithm for best decision

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [189] is widely used multi criteria based decision-making algorithm that compares resources according to alternative criteria and sort them on basis of their allocated weight. It calculates the normalized decision matrix. Consider the number of alternatives is n, q is the number of comparison metrics. We have taken five metrics for hospitals that are *budget, availability of ICU, normal beds, blood bank availability and oxygen supply*. User's location, SpO_2 Level, BP Level, preference and budget have been treated as user parameters for querying the smart API system. As a part of intelligent decision making system, saving a life has been prioritized. Therefore, medical health related parameters are assigned with higher weights than medical expenses. The mathematical formulation for TOPSIS in finding suitable hospital among much availability is formulated as follows. Let normalized decision matrix, D_{ij} is determined by equation 5.9, considering i number of hospitals and j number of patient's criteria.

8.
$$D_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{r} d_{ij}^{2}}} . \omega_j (i = 1,2, \dots n; j = 1,2, .. q) \tag{5.9}$$

9.
$$H = \begin{bmatrix} H_{11} & . & H_{1q} \\ . & . & . \\ H_{n1} & . & H_{nq} \end{bmatrix} \tag{5.10}$$

H is hospital evaluation matrix. Where n is the number of Hospitals, $d_{ij} = A_j(i)(i = 1,2, \dots, n; j = 1,2, .. q)$ and $w_j$is weight for the metrics.

10. Calculate positive $I_j^{+ve}$and negative I_j^{-ve}ideal solutions for j;

$$I_j^{+ve} \begin{cases} \max\{D_{ij} | i = 1,2, \dots n\}, & j =\in P_p \\ \min\{D_{ij} | i = 1,2, \dots n\}, & j =\in C_c \end{cases}$$

$$I_j^{-ve} \begin{cases} \min\{D_{ij} | i = 1,2, \dots n\}, & j =\in P_p \\ \max\{D_{ij} | i = 1,2, \dots n\}, & j =\in C_c \end{cases} \tag{5.11}$$

Where P_p & $C_c$are profit and cost attribute respectively.

11. Distance for each alternative i to its positive ideal solution and negative ideal solution

$$Dis_i^{+ve} = \sqrt{\sum_{j=1}^{q} (D_{ij} - I_j^{+ve})^2}, \qquad Dis_i^{-ve} = \sqrt{\sum_{j=1}^{q} (D_{ij} - I_j^{-ve})^2}$$

(5.12)

12. Hospital importance is more if its value is closer to the positive ideal solution and farther from the negative ideal solution. The TOPSIS value which denotes relative closeness to the ideal result is

$$Highest_i = {Dis_i^{-ve}} \Big/ {Dis_i^{+ve} + Dis_i^{-ve}} \tag{5.13}$$

$Highest_i$ ranks denote the preference order. The range of values $Highest_i$ stands from 0 to 1. The larger score denotes the closeness to ideal solution for resources. In next phase, highest scored alternative is chosen as destination. Firefly algorithm is used to decide the optimal path.

A. Firefly Algorithm to determine optimal route direction

Firefly Algorithm is a well-known nature inspired, Meta heuristics algorithm that is used to find out optimal path for destination [190]. Fireflies produce light flashes and through its brightness neighbouring fireflies or preys attract towards them. In this work, this algorithm is used to decide shortest path between patient location and healthcare destination. In Dijkstra, most popular path planning algorithm where destination cannot be changed and edge cost is fixed. But, in this particular application destination change is very normal. This clause makes firefly the suitable choice [191].

Firefly operation has two important performance metrics which are light intensity and attractiveness. Light intensity depends on the distance from the viewpoint. The light intensity decreases with increasing distance.

$$L(d) = L_0 e^{-\alpha {d_{ij}}^2} \tag{5.14}$$

L is the light intensity, L_0 is initial light intensity, α is light absorption coefficient and d is the distance between firefly i and j. Attractiveness (A) is proportional to the light intensity that is fetched by other fireflies.

$$A = A_0 e^{-\alpha {d_{ij}}^2} \tag{5.15}$$

A_0 is the initial attractiveness when $d = 0$.

In this case, we have represented each candidate path location as firefly. Let, each path has n main coordinate points in the (x, y) plane. So each firefly (path) is denoted as $x_i = (x_1, y_1, \dots, x_n, y_n)$

Here, i means the i^{th} firefly. The distance between source and destination at positions x_i and x_j is defined as

$$d_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{r=1}^{d} (x_{i,r} - x_{j,r})^2} \tag{5.16}$$

$x_{i,r}$ is the r component of the spatial coordinate x_i of the i^{th}firefly.

$$d_{ij} = \sqrt{(x_i - x_{j,})^2 + (y_i - y_{j,})^2} \tag{5.17}$$

The movement of a firefly i who is attracted by a more attractive means brighter firefly,

$$x_i^{t+1} = x_i^t + A_0 * e^{-\alpha d_{ij}^2} * \left(x_j^t - x_i^t\right) + \mathrm{a}\gamma_i^t \tag{5.18}$$

Where, the first term is the current position of a firefly, the second term is dedicated for observing a firefly's attractiveness to light intensity understood by nearby fireflies, and the third term is used for the random motion of a firefly if there are not any brighter ones presents.

B. Web Application for final recommendation

Figure 5.10 depicts the underlying architecture of web applications. User requests via Representational State Transfer (REST) [192], an architecture for Application Program Interface (API). HTTP calls with the Java-Script Object Notation (JSON) content format to the WildFly server. This is an open-source local server. This server interfaces with real-time databases such as AWS in this case and vice versa.

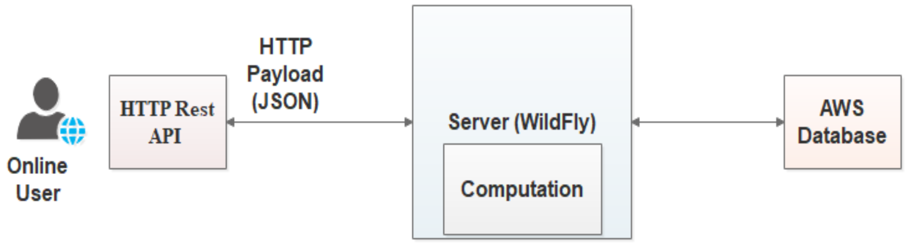


Figure 5.10 Web API Architecture

5.3.2 Performance Evaluation

We have used the Eclipse integrated development environment (IDE) to write the code in Python and Java. Our objective is to first get the hospital ranking matrix using the TOPSIS algorithm. Table 5.2 shows the final TOPSIS output, which decides appropriate recommendations for hospitals based on patients' requirements. The highest score means the best suitable hospital among all. Figure 5.11 represents a spider chart, which is used to display multi-dimensional data clearly. The chart comes from a weighted normalized matrix.

Table 5.2: Hospital Ranking based on TOPSIS

Alternatives	Location	TOPSIS Score	Hospital Rank
Hospital 1	22.590, 88.398	0.48	4
Hospital 2	22.602, 88.406	0.36	5
Hospital 3	22.566, 88.410	0.25	6
Hospital 4	22.563, 88.399	0.85	1
Hospital 5	22.573, 88.401	0.64	2
Hospital 6	22.626, 88.421	0.55	3

It distinctly depicts parameter values for different hospitals. For example, Hospital 3 has high budget amount and hospital 4 tops in number of bed counts. Next sets of results we have generated in open source traffic simulator SUMO. The VANET simulation platform has been used in this work to apply Firefly algorithm for finding optimal path direction for patient to reach destination hospital. The parameters used for this work is given in Table 5.3.

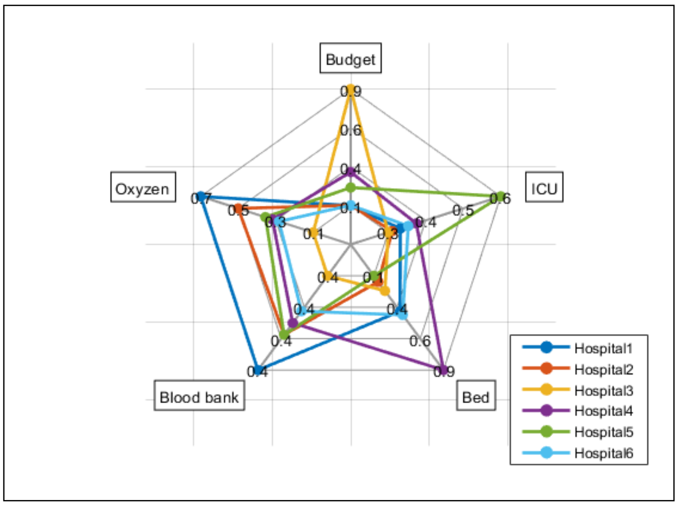


Figure 5.11: Spider chart for weighted normalized matrix of TOPSIS

Table 5.3: Simulation Parameters

Parameters	**Values**
Area	5Km * 5 Km
Speed Limit	40 Km/h
No. of vehicles	50-200
Car following model	Krauss Model of SUMO
Vehicle length	5-10 m

We have imported real street models from Open Street Map (OSM) which is also an open source. We have explored different traffic density scenarios and termed them as normal, moderate, and congested traffic conditions according to an assigned threshold value of traffic. Random numbers of vehicles arrive in the network at every periodic time interval. The Firefly algorithm is applied for each aforementioned scenario to *estimate travel time for the destined route*. Figure 5.12 shows the plot for the travel time comparison for each scenario.

According to the user health status and location shown on the left side of Figure 5.13 web API recommends the hospital name, location, and path on the right side. User can provide their preference and according to the resource availability, the system will refer to hospital details. Here, user preference is given Beleghata ID Hospital but due to resource scarcity and user health parameters, another option has been recommended for Apollo Hospital. In Figure 5.14, the preferred hospital is recommended when resources are available.

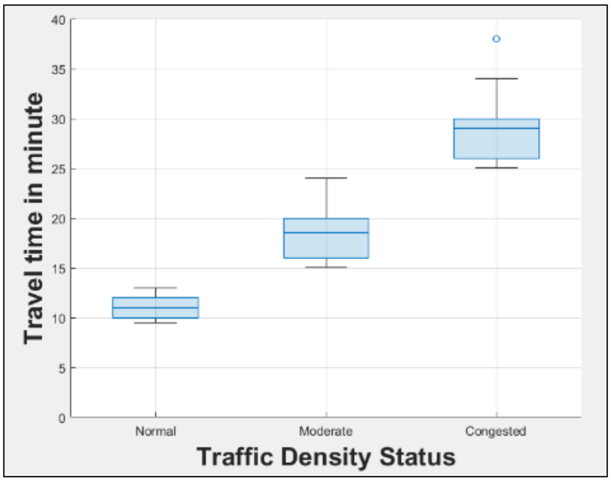


Figure 5.12: Comparison of Travel time for varyinhg traffic density

It means if the resource is available then the system will suggest the best destination according to the comparison criteria in the TOPSIS matrix. As per the description we have used an open street map from Google to SUMO for VANET path planning. Figure 5.15 (a) shows the patient's vehicle carrying to Appllo hospital at first as per the recommendation from home location 22.606, 88.416. Later in Figure 5.15 (b), it is shown that the route direction has been changed to Beleghata ID hospital in between the trip from home to Apollo hospital. The recommendation system changed it's decision as per the instant availability of the requested hospital Beleghata ID from the patient party. User can change the destination which is more suitable according to the present situation. This is the best part of the Firefly algorithm that cannot be achieved by Dijkstra. Google maps uses dijkstra algorithm which is good enough for static environment. It follows blind search which rises its computational time complexity upto $O(n^2)$ where n is the population size [193].

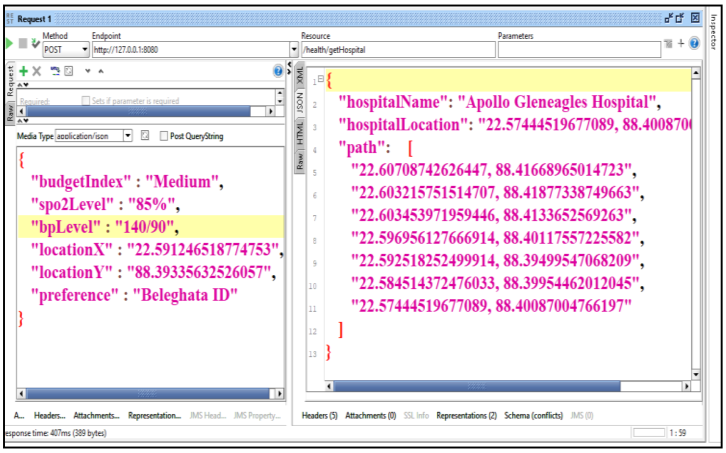


Figure 5.13: Screenshot of System output with recommendation for Apollo Hospital and it's route

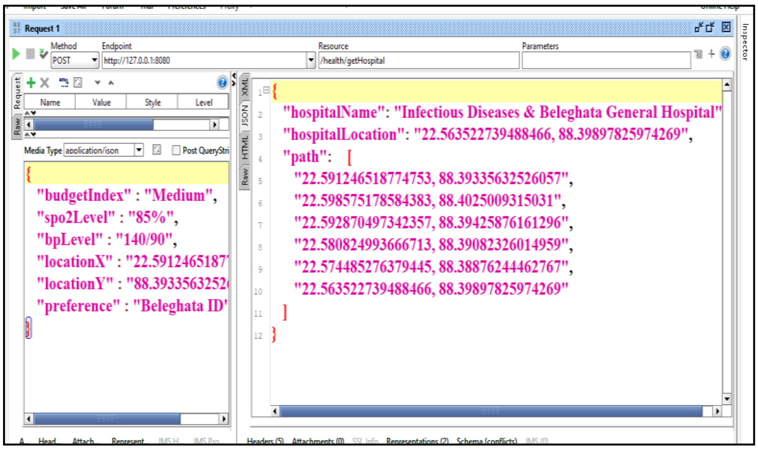
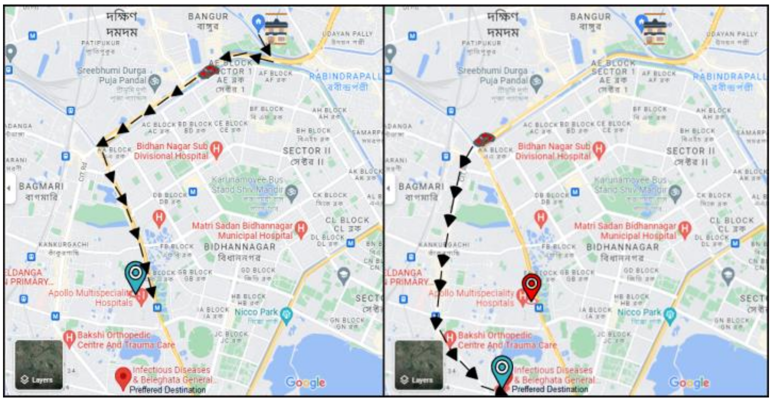


Figure 5.14: Screenshot of System output for requested Beleghata ID route



(a) (b)

Figure 5.15 (a) Route to the recommended destination Apollo Hospital (b) Destination changed due to resource availability

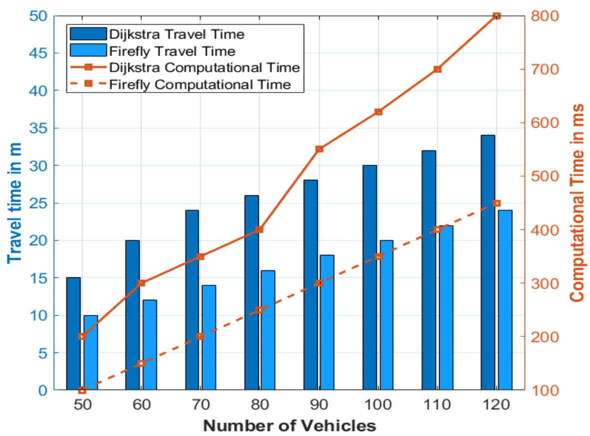


Figure 5.16: Comparison of Dijkstra and Firefly Algorithm

Metaheuristics algorithms are less complex and less difficult to perform. With relatively big n the complexity of the Firefly algorithm is $O(nt(logn))$ where t represents the number of iterations [194]. We have observed traffic simulation for both Dijkstra and Firefly algorithms in similar environments. In Figure 5.16, it depicts that the Firefly algorithm outperforms

Dijkstra with respect to travel time as well as computational time. The average percentage of reduction in travel time and computational time in the case of the Firefly algorithm are 34% and 43% respectively in comparison with the Dijkstra algorithm.

5.4 Chapter Summary

This chapter appraises the ongoing problem of traffic congestion and road safety in Indian metro cities and significantly develops a framework with the research objective of implementing an Intelligent Transport System. In this research, the effectiveness of VSL control traffic metrics such as total travel time, and speed is compared with and without any speed limit control scenarios. VSL provides a stable velocity throughout congested hours (>319 cars/km) for our proposed method through which the objective of the chapter is well established. Our proposed controlled model is evaluated with varied path length and increasing buffer time validating the model with the outcomes.

Further, in this chapter, we have shown a way of utilizing useful data under ITS for finding emergency health care unit as per the patient condition and request generated by the patient party. The systematic procedure is clearly described with appropriate results to serve the purpose. TOPSIS algorithm provides the suitable hospital with ranking, and Firefly in integration with SUMO provides the best route to the destination with an estimated time of arrival. A Web API system is created that connects real-time databases like AWS and processes it. Mobile applications can also combine with it. Whenever, the real-time database alters status, which reflects in the ranking list as a result, the recommended hospital also differs. In between the trip whenever this situation occurs firefly optimization changes the destination following the situation and re-routes the vehicle. We have also ensured comparative analysis between the Dijkstra and Firefly algorithms in terms of travel time and computational time. Both the contributory works ensure the lesser travel time, which increases the efficiency of the transportation sector. However, environmental pollution is an immensely important challenge faced by ITS which has been taken up in Chapter 6.

- Publications from this chapter

1. Sreya Ghosh, Iti Saha Misra, "Controlled Speed Limiting System for Congestion Mitigation for Smart City Design" , In2020 IEEE Calcutta Conference (CALCON) 2020 Feb 28 (pp. 225-229). IEEE.
2. Sreya Ghosh, Iti Saha Misra, Tamal Chakraborty, "Developing an Application for Intelligent Transportation System for Emergency Health Care" In2022 IEEE Calcutta Conference (CALCON) 2022 Dec 10 (pp. 39-43). IEEE.

6

Design and Analysis of ITS Systems for Reducing Travel Time, Carbon Emission and Fuel Consumption

Design and Analysis of ITS Systems for Reducing Travel Time, Carbon Emission and Fuel Consumption

Outline of the Chapter:

6.1 Introduction

"Environmental pollution is an incurable disease. It can only be prevented." —

Barry Commoner, American cellular biologist, ecologist, and politician

After suitably studying, optimizing, and implementing the RSU deployment framework in Chapter 3, designing QoS-enhanced VANET routing algorithms in Chapter 4, and also concentrating on VSL systems and emergency path planning in Chapter 5, the next important objective is to design and implement ITS that is capable of managing and controlling traffic to facilitate congestion and pollution mitigation. This is envisioned to address the basic challenges catered by ITS which include rapid rise of the increasing traffic, estimating it accurately and tackling it according to the available road resources. Therefore, this chapter deals with intelligent vehicle re-routing that uses multi-layer vehicular networks and machine learning frameworks.

Unplanned development comes with social, economic, and environmental degradation. The consequence of an exponential rise in the number of vehicles induces traffic congestion and excessive pollution. The existing road resources cannot handle the tremendous traffic demand of today's rapidly developing economy. Massive traffic congestion and resulting traffic jam slow down the development of urbanization [195]. To encounter these issues Intelligent

Transportation System (ITS) performs a pivotal role due to its enormous applicability [196]. Enhancing safety, and vehicular speed and reducing resource consumption, travel time, and traffic jam are the primitive goals of implementing ITS [197].

Covid pandemic increases the tendency of buying private cars among consumers to maintain social distancing. This scenario boosts the number of private vehicles more than public transport in roadways, which takes favourable part in congestion occurrence [198]. As the dedicated route of public buses cannot be altered, the remaining transportation should be planned according to the rapidly changing traffic circumstances.

Intelligent Transport System (ITS) is a widespread tool that handles real-time traffic, which depends on data acquisition from vehicles, roadside units, and various traffic sensors. These entities make a collaborative vehicular network among themselves [199]. The growth of ITS depends on the high degree of traffic throughput and flexibility which is ensured by an efficient and accurate path-planning method. Unplanned road structure, continuous surge of vehicles, and inadequate carrying capacity introduce enormous challenges to implementing efficient path planning algorithms [200]. Path planning plays a pivotal role in navigation systems that search global maps to get a suitable route between origin-destination pairs by utilizing planning algorithms such as Dijkstra, A-star (A*) along others.

Dijkstra is a pioneering algorithm that is used to search the shortest path between two vertices because of its optimal capability for global planning [201]. Dijkstra algorithm does not consider the direction it is going which may results to explore the vertices that are not even close to the target node. This expands the shortest path searching time. An extension of it is A* (A-star) which manages to achieve better results by means of heuristics to supervise its searching process [202]. The heuristics provide a sense of directionality in searching the shortest path. Global path planning algorithms are more appropriate for static environments. For complex and uncertain environment like transportation network, their efficiency is compromised.

Accordingly, in this chapter, a heuristics cost based re-routing of cars is proposed than not only consider shortest distance but also condition and frequency of usage of a route. Congestion avoidance and travel time reduction eliminate waiting time of vehicles. This reduces the acceleration and deceleration of vehicles, resulting in reduced CO_2 emission and fuel consumption. A road network is expressed as a connected graph where intersections and roadways are represented as nodes and edges respectively. Another significant contribution of the proposed approach is the segregation of public transport and private vehicles. As public buses follow fixed route and in between stoppages, routes remain pre-determined for the services. Private vehicles are rerouted in accordance with the real-time traffic condition, which delivers efficient transportation system.

The functionality of ITS is built upon the collaborative interoperability among vehicles, roadside infrastructures, and backbone cloud architectures which depends on their communication and computation capabilities [203]. The present era experiences the rapid evolution of communication and networking innovations namely 5G networks, mobile edge computing (MEC), and so on. They hugely boost the capability of ITS to gather requisite data and establish secure connections among the components [204] [205]. To explore the entire possibilities of ITS, it is essential to embrace advanced data analytics methodologies like machine learning. One of the most emphasized ITS applications is promoting a route planning system that focuses on congestion prediction and planning vehicular trajectory according to them. The accuracy of the predicted traffic model is the crucial key factor to ensure the efficiency of the route planning system. When rerouting of vehicles is done without the awareness of the local and global traffic situation then it increases the travel time and fails to achieve its purpose [206].

Route planning systems (RPS) can be categorized as static and dynamic based on their potential for data collection. Static RPS processes fixed traffic data to plan the route for vehicles and it does not update with time. These datasets are generally historical information and are not able to provide optimal routes for vehicles. On the contrary, dynamic RPS uses real-time data from traffic sensors, detectors as well as historical data to mitigate congestion. They are classified into distributed, centralized, and hybrid systems [207]. In a centralized architecture, the central server solely controls the entire traffic and performs computational tasks. It increases the excessive computational load, processing power, enormous delay, and bandwidth requirement. This creates a negative impact on the performance and this architecture is only suitable for smaller regions. However, distributed systems use short-range communication among vehicles, RSUs, and functions individually. Although they consume less computational power but have inadequate global knowledge. This is not a practical idea to use them to manage millions of vehicles in an urban area [208]. The central server obtains aggregated information from the entire region and develops global traffic updates whereas distributed nodes collect traffic data, process it, and generate local awareness as well as share the knowledge to a central server. This hybrid architecture resolves factors like processing delay, bandwidth overhead, and high complex computational power [209] [210].

RPS systems use a single metric to suggest optimal paths for vehicles, which is not effective in real-world scenarios. Only the shortest distance or lowest travel time-based RPS is unrealistic. Instead, the multi-metric-based system utilizes various functional parameters for generating the best possible route for vehicles [211]. Motivated by the advantages of the hybrid multi-metric model, we have proposed an RPS namely RATM-FL. Federated learning (FL) facilitates the machine-learning paradigm to be trained in a distributive manner [212]. In FL, the assembly of edge devices such as RSUs, vehicles, etc., trains a global model at the central server cooperatively while preserving the complete training information locally at the edges.

Conventional FL models assume that in each iteration all the participating clients transmit the trained data to the server and receive the trained data from the server simultaneously irrespective of their significance in the present scenario [213]. A random set of clients participate in typical FL whereas some of them suffer from poor connectivity, and resource scarcity that affects overall system performance. As each participant has different training times and dataset sizes it is not a feasible solution to accommodate all of them for uploading the training data to a central server for each communication round. The participation of less significant clients may lead to energy wastage and communication overhead [214]. For dynamic vehicular networks, trained model updates from the most influential regions are highly important for effective traffic management. Therefore, conventional FL models are impractical for vehicular networks [215]. The limitations of existing FL systems are encountered through our proposed model RATM-FL. In this paper, we opt for an FL-based framework for traffic management where the central traffic cloud centre can dynamically select the subset of roadside units according to their significance. We prioritize and select RSUs with the highest profits, which are determined by the amount of traffic they have tackled. After a certain communication round, TCC waits for a threshold time limit and accesses the local model only from selected RSUs based on the information gathered from the vehicles and then transmits the trained global models to the FL participants. Each selected RSU is allocated a designated sub-channel to send their trained model updates.

6.1.1 Contributions of this chapter

The significant contributions of this chapter are therefore summarized as follows.

1. The transportation network is represented as vertices and edges, where vertices are the junctions and edges are the connecting roadways. An enhanced version of the renowned A^* algorithm is proposed that generates a balanced re-routing of vehicles according to the real-time road condition and avoids recurrent use of a particular road.

2. In this work, we have used only private vehicles for re-routing, as public vehicles have to follow their predetermined route. It is established through performance evaluation that enhanced A^* outperforms traditional A^* and Dijkstra in terms of travel time, waiting time, vehicular speed, and environmental pollution emission.
3. Thereafter, A novel FL-based traffic management system RATM-FL is introduced for improved traffic management. The proposed framework predicts traffic congestion and re-route cars by incorporating an RSU and cloud server-based paradigm. RSU receives the traffic data from vehicles and detects the congestion level of roads rather than transmitting all the data to a central server; it uses the BiD-LSTM framework to predict traffic information.
4. Then, the FL framework is established for global model training at a central server, allowing the model to learn from multiple distributed RSU data. Considering the necessity of optimal RSU placement, we use the central server to plan routes for vehicles when they are not in the coverage area of any RSU or the destination of the vehicle is outside of RSU coverage.
5. To alleviate the hazards of random selection of FL participants, we have designed an integer linear program-based model that maximizes RSU selections based on the higher profits which depends on the amount of traffic they have encountered.
6. The result analysis section shows the effectiveness of the proposed method. Experimental results demonstrate the superiority of our model in comparison with baseline methods. Therefore, RATM-FL successfully has decreased traveling time, waiting time, CO_2 emission, and fuel consumption of all vehicles in the whole region. Additionally, the average speed of the vehicle is also increased.

6.1.2 Chapter Organization

This chapter is organized as follows. Section 6.2 presents the proposed Enhanced A^* algorithm with an overview of the system architecture in subsection 6.2.1. This is followed by an in-depth discussion of results in subsection 6.2.2. The next remarkable addition of this chapter is demonstrated in section 6.3 followed by the proposed work and performance evaluation in subsections 6.3.1 and 6.3.2 respectively. The chapter is concluded in Section 6.4.

6.2 Enhanced A* Algorithm

The huge outburst of vehicles on the road cause enormous traffic congestion and environmental pollution, which affect human health. Appropriate re-routing of vehicles can be a savior to manage congestion and reduce environmental degradation. A novel re-routing scheme named Enhanced A* algorithm is being proposed that uses the shortest distance and real-time road conditions and traffic information to re-route vehicles. Proposed algorithm outperforms while analyzing it with well-established path planning algorithms A*and Dijkstra with respect to waiting time, CO_2 emission, fuel consumption, travel time and vehicular speed.

6.2.1 Proposed Methodology

System Architecture

Intelligent path planning in VANET needs vehicle-to-vehicle and vehicle-to-infrastructure communication for transferring information among vehicles and road infrastructures. An amendment of 802.11 is established for rapid vehicular communication known as 802.11p [216]. The system model consists two main building blocks on board units (OBUs) quipped vehicles and Roadside unit (RSUs). RSU broadcasts a beacon packet at every periodic interval to all the vehicles within its range. The corresponding vehicles that received the beacon send a reply beacon packet to the attached RSU including GPS coordinate, velocity, identification and route information. Figure 6.1 illustrates the beacon packet format of vehicles. Each vehicle has an individual identifier that defines its type. RSU is dedicated to analyze the road, vehicle types and traffic condition based on the information fetched from vehicles and provides convenient route to private vehicles.

Flag bit	Vehicle Identity	Position	Speed	Road ID	Source ID	Destination ID	Timestamp

Figure 6.1: Beacon packet format

ITS is a combined methodology of transportation resources for delivering reduced congestion and pollution and improve traffic efficiency. Further section explains proposed algorithm.

A-star Algorithm for finding shortest route

A-star algorithm intends to search shortest path from source to destination point known as one of the best path planning algorithms. Searched paths with minimum cost value is selected as shortest path. It performs better due to its heuristic searching in combination with shortest path searching. According to Figure 6.2, S is source node and G is goal node. N number of intermediate nodes connects both the nodes. From S to intermediate nodes the actual path cost is known which is represented by $g(n)$ and from n to G, the path cost is estimated which is represented by $h(n)$. Total cost function from source node to goal node is calculated by

$$f(n) = g(n) + h(n) \quad (6.1)$$

The efficiency of A-star algorithm depends on the accuracy level of heuristic value. The lowest value of $f(n)$ is determined the shortest path [190].

The algorithm maintains two lists as Open and Closed. Open list contains the nodes that are discoverable but not accessed yet and closed list holds the nodes that have been traversed already. Open list is assorted by the heuristic function according to the result of cost function. Minimum cost is selected for each node and step-by-step optimal shortest route to target is achieved.

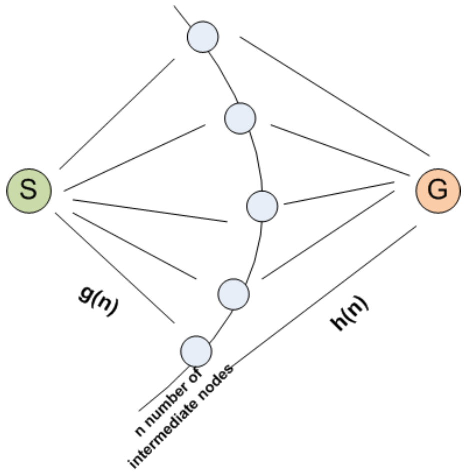


Figure 6.2: Illustration of A-star

Enhanced A Algorithm*

In traditional A-star algorithm cost function is calculated using the distance parameter. But in real time scenario distance is not enough to estimate an optimal route. A route may not be feasible enough due to some catastrophic event. $fe(n)$ is used as feasibility parameter of the road for a particular interval of time. When a route is encountered with an accident or procession $fe(n)$ value increases beyond the threshold for that route. Lower the $fe(n)$ value means route is more suitable and shorter. In our proposed A-star modified heuristic is provided as $h^*(n)$.

$$f(n) = g(n) + h^*(n) \quad (6.2)$$

$$h^*(n) = h(n) \times fe(n) \quad (6.3)$$

$$fe(n) = 1 + S_f - \frac{N_A}{N_C} \quad (6.4)$$

$fe(n)$ is real time feasibility of the route. S_f indicates selection factor whose value is ($0.1 \leq S_f \leq 1$), N_A is the number of slots available in the route and N_C is the capacity of the route. S_f is the lowest for a particular route when the route is not selected once and it is incremented by 0.1 whenever the route is selected as alternate route. When a route is affected by an environmental or accidental hazard immediately its value is set to 1 so that it is not considered for the re-route scenario until the problem is resolved. According to A-star, minimum cost path is selected as shortest path. This can perform well when traffic density is moderate but when huge amount of traffic is coming traditional A-star fails. More number of traffic is coming a greater number of traffic are needed to be re-routed. In this situation the shortest route has to handle huge traffic flow which makes it congested too and the purpose of traffic management goes to vain. Therefore, in modified A-star all the possible alternate routes are considered and feasibility value is changed dynamically with the traffic density of the route. When a vehicle is re-routed through the best feasible and shortest route the next node vehicle is not followed the same route means it always checks the previous node's selected route. In this way, best possible load balancing is done among all the alternate routes.

Algorithm 6.1: Enhanced A*

Input: O, D, $[T = (n, e)]$, $[v_1, v_2 .., v_n]$

Output: $Route[n]$, D

Initialize
Route[n] ←add O;
while (current_node! = D)
identify next_nodes[n]
if next_node[n] is not empty **then**
for (n = 1 *to N*) **do**
current_weight←g(n) + h*(n)
if lowest_weight = 0 **then**
lowest_weight←current_weight
next_node ← node
else if lowest_weight>current_weight **then**
lowest_weight←current_weight
next_node← node
else if lowest_weight = current_weight **then**
if Node is used for Last Route = false **then**
next_node← node
end if
end if
endfor
Route [n] ← add next_node
current_node←next_node

22. **else**
23. go back to previous node
24. **end if**
25. **end while**
26. **return** Route[n]

Vehicles are denoted as $[v_1, v_2.., v_n]$ in a transportation network $T = (n, e)$ where $[n_1, n_2.., n_N]$ are set of intersections and $[e_1, e_2.., e_N]$ are set of connecting roadways. Each vehicle belongs to an origin (O) and destination (D) pair $(O, D \in n)$. Algorithm 6.1 describes route discovery where source node in as added in Line 1. If the current node is not the intended destination, then it should continue its route discovery, which initiates from line 2. In the current node, it identifies all the adjacent nodes towards the route inline 4. If it has adjacent nodes, then it calculates weight for each adjacent nodes in. If the latest encountered node has the lowest weight, then it becomes the chosen node, but if the latest encountered node has similar weight of the lowest one, then for load balancing it checks if it has been used too much. If it is overused, then it chooses the prior one. After that, the lowest node is being added to route discovery array. At last, it's returns route in line 26.

6.2.2 Results and Discussion

"Simulation of Urban Mobility" (SUMO) is an open-source, microscopic traffic simulation software where each vehicle is designed explicitly to implement large traffic networks and address a huge set of traffic management scenarios [217]. NS3 is a network simulator used to simulate the underlying communication architecture. TraCI (Traffic Controller Interface) is a module provided by SUMO sets the vehicular speed, traffic signal timings etc. To figure out fuel consumption and CO_2 emission we have taken *Handbook Emission Factors for Road Transport V.3 (HBEFA3)* based emission model of SUMO. It is a statistical model used to compute fuel consumption and CO_2 emission, which depends upon acceleration and vehicle speed. Road network is not only designed on Netedit package of SUMO but also on realistic OSM (open street map). OSM is transformed to xml format to make it compatible for SUMO. OSM is a free and editable map of the world, released with an open-content license (Open Street Map Wiki, 2016a). Figure 6.3 depicts the step-by-step operation in SUMO.

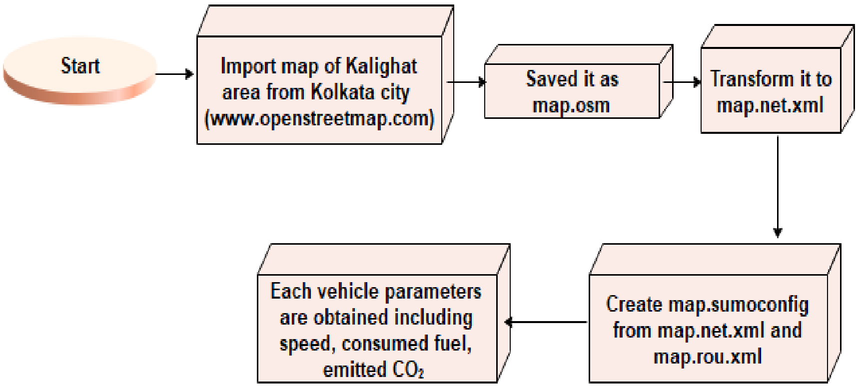


Figure 6.3: Stepwise block diagram of simulation environment

Simulation Environment

First experiment scenario is a 10 × 10 grid network created in SUMO Netedit (network editor) with 100 nodes and 360 edges. In Figure 6.4, grid network in shown in the left side and the red circle is zoomed in the right sight. As Indian road structure is unplanned, experiment should perform in realistic transportation map.

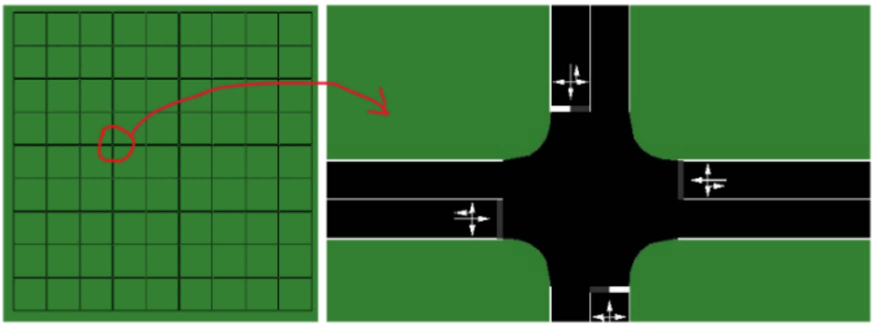


Figure 6.4: Grid based simulation created in SUMO

Second experiment scenario is an imported map from OSM of Kalighat area from Kolkata city which is visible in Figure 6.5. The road network parameters are described in table 6.1. The source point in geographic coordinate system is (22.52244, 88.36255) and the destination point is (22.5185, 88.3472). Traffic simulation parameters are summarized in table 6.2.

Table 6.1 Network Parameters

Parameters	Value
Area	$5Km^2$
Nodes	350
Edges	1068

In Figure 6.6, it is visible that two types of vehicles are used in simulation where yellow-coloured vehicles are treated as private vehicles and red coloured vehicles are treated as public transport.

Figure 6.5: OSM map and imported network in SUMO

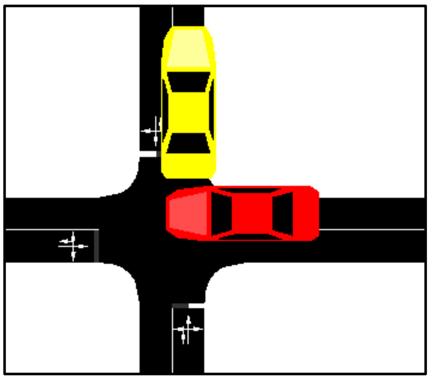


Figure 6.6: Vehicle type segregation in SUMO

Table 6.2 Simulation Parameters

Parameters	**Values**
Minimum Speed	0 Km/h
Maximum speed	40 km/h
Acceleration	4 m/s^2
Deceleration	-3 m/s^2
Safety Gap	2m
Car following model	Krauss
Simulation Time	3600s

Performance Evaluation Metrics

The number of vehicles is linearly proportional with waiting time, fuel consumption, CO_2 emission and travel time, which consecutively escalate traffic congestion whereas it is inversely proportional with average speed of the vehicles. Therefore, these five metrics are analysed for performance evaluation of proposed re-route approach. Figure 6.7 describes the performance evaluation metrics in detail. As SUMO is a microscopic traffic simulator that provides individual vehicle dynamics [218], in the outcome average values of simulation parameters are used which is elaborated in Figure 6.8.

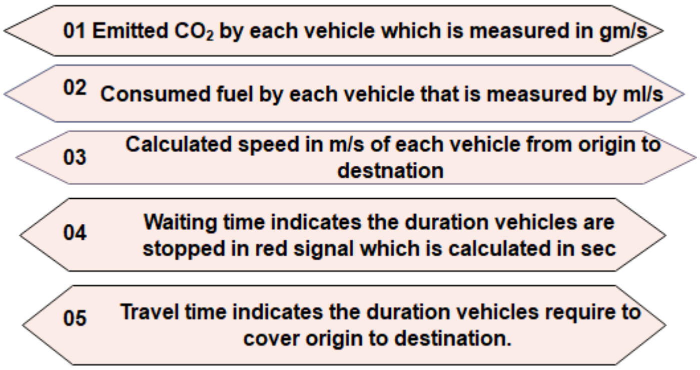


Figure 6.7: Metrices used for performance evaluation

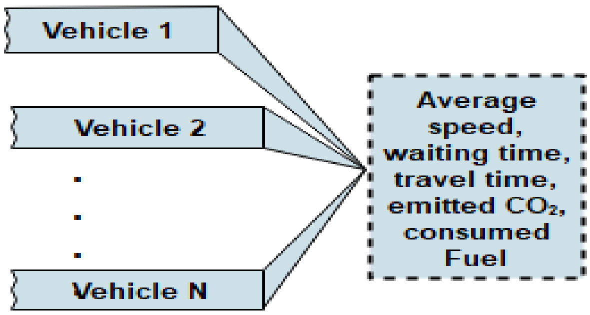


Figure 6.8: Average value generation of simulation parameters

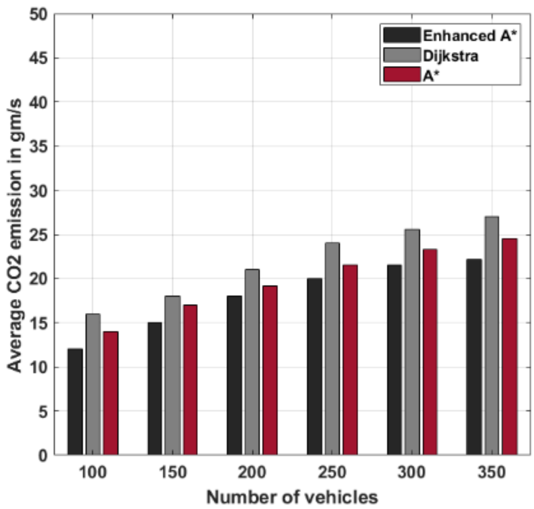


Figure 6.9: Comparison of Enhanced A* with Dijkstra and A* based on average CO_2 emission vs. number of vehicles

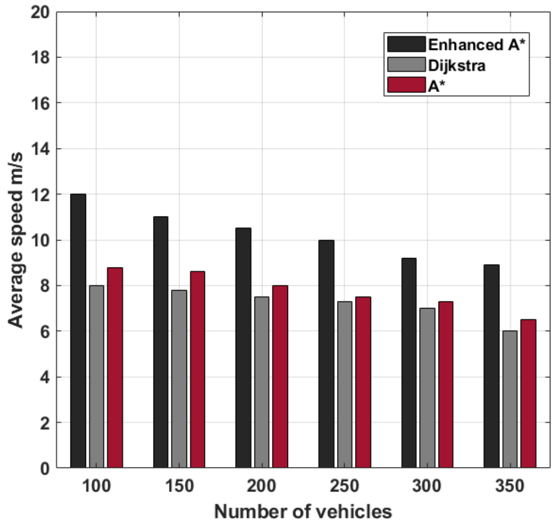


Figure 6.10: Comparison of Enhanced A* with Dijkstra and A* based on average speed vs. number of vehicles

Simulation Outcome

Simulation is done based on varying numbers of vehicles for two experimnts. Results are observed for Dijkstra, A* and Enhanced A* based on five performance parameters that are fuel consumption, CO_2 emission, travel time, waiting time, and vehicular speed. Figures 6.9,6.10, 6.11, 6.12, 6.13 depict the graph of average CO_2 emission vs. the number of vehicles, average speed vs. a number of vehicles, average fuel consumption vs. number of vehicles, average travel time vs. the number of vehicles and average waiting time vs. a number of vehicles respectively.

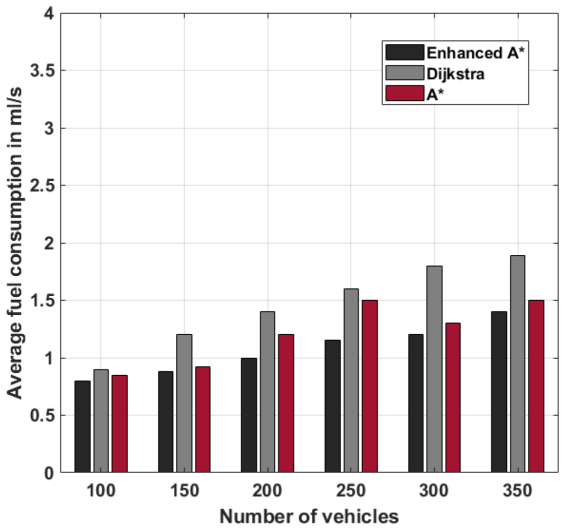


Figure 6.11: Comparison of Enhanced A* with Dijkstra and A* based on average fuel consumption vs. number of vehicles

It can be analysed from Figures 6.9, 6.11, 6.12, 6.13 that average CO_2 emission, fuel consumption, travel time and waiting time are reduced for enhanced A* in comparison with Dijkstra and A*. Figure 6.10 describes that average vehicular speed is increased for enhanced A* in comparison with dijkstra and A*.

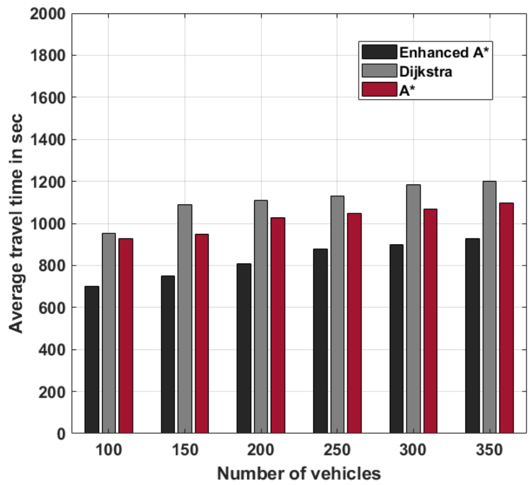


Figure 6.12: Comparison of Enhanced A* with Dijkstra and A* based on average travel time vs. number of vehicles

Discussion of Outcomes

Enhanced A* shows better performance than Dijkstra and A* algorithms. As enhanced A* uses alternate routes on the basis of road conditions and frequency of usage of a particular route. Conventinal A* considers the lowest cost of a route which only depends on the shortest distance and Dijkstra introduces the overall path to the vehicle whenever it begins its trip.

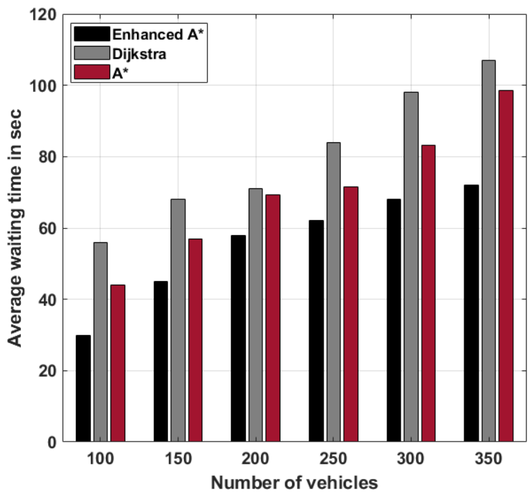


Figure 6.13: Comparison of Enhanced A* with Dijkstra and A* based on average waiting time vs. number of vehicles

6.3 An Improved Intelligent Traffic Management for Smart Cities Using Federated Learning-based Congestion Predictions

Due to rapid urbanization, the transportation sector facing the problem of dealing with tremendous traffic congestion affecting negatively the economy and environment. One of the effective solutions to resolve congestion is the building of intelligent route planning systems. Nowadays machine learning models are being used for congestion prediction in many cases. In this paper to address this challenge, a novel, multi-layer, roadside infrastructure, and cloud server-based traffic management system named RATM-FL, an RSU-assisted traffic management system using federated learning is introduced. Roadside infrastructure such as road side unit (RSU) is used to obtain and process local traffic information through which it detects and predicts the congestion status of routes and manages traffic within its coverage area. It also transmits weighted traffic information to a cloud server that has a unique ability to build a global traffic prediction model. RSU deployment is a budget-constraint task; the cloud server handles the areas that are not covered by RSUs. As all the RSUs are not performed as equal contributors, RATM-FL follows traffic condition-based RSU selection in the FL framework. For the optimized selection of RSUs, numbers of vehicles present in the RSU coverage area along with energy consumption are considered. Dynamic selection of RSUs will reduce energy consumption without compromising the system performance. We build the intelligent selection of RSUs as an integer linear program. In each communication round the number of RSU participants in RATM-FL is maximized given each RSUs importance in the present traffic scenario. Performance evaluation is carried out on open-source traffic simulator SUMO and python. The simulation outcome illustrates that the proposed RATM-FL framework outperforms in comparison to state-of-the-art solutions available in the literature at present by reducing travel time, fuel consumption, and CO2 emission.

6.3.1 Proposed framework

A. System Model

This subsection demonstrates the underlying architecture of our proposed hybrid multi-metric RPS system and delivers a lucid overview of traffic prediction framework that is based on federated learning.

Figure 6.14 narrates the underlying system architecture of RATM-FL. To facilitate the proposed approach, the system architecture incorporates a cloud-based traffic management server, roadside infrastructure along with vehicles. Collaboratively, they are engaged for gathering traffic information in periodic time interval to provide required services to commuters. A centralized traffic control centre (TCC) has computing capability, which is used to store, process and manage traffic data. Roadside units act as transceiver systems and are deployed in road intersections to provide necessary services. RSUs generally have more computation and communication capability than vehicles [219]. As RSU deployment and maintenance is an expensive task they should be placed optimally throughout the region.

In Chapter 3, identification of influential intersections for optimal RSU placement (IIA-ORD) is achieved, followed in this work to build the vehicular network [220]. In a rapid vehicular environment, communication is vital in accomplishing the scheduled task. Vehicles can communicate with RSUs through V2Vor V2V2I links [221]. Two types of wireless communication is available in the system model (figure 6.1). Dedicated Short-Range Communication (DSRC) is applied for data transmission between vehicles and RSUs and vice versa. Besides that, long-range communication means cellular communications are executed between RSU, vehicles and central server when required through macro base stations [222]. According to the proposed framework, both the RSUs and TCC are capable of predicting traffic and provide route guidance to vehicles. As RSU covers a small area, it can only provide optimal routes to vehicles if the destination is within its coverage range. Contrarily, TCC takes the responsibility to suggest the best route to vehicles when the destination is outside RSU's coverage, as it has the global knowledge of the traffic scenarios. RSUs are deployed in the important intersections so whenever congestion occurs in those heavily influenced areas it can be addressed by the RSUs instantly. Otherwise, when congestion affects the regions, which are not covered by any RSUs, TCC calculates the best route for vehicles.

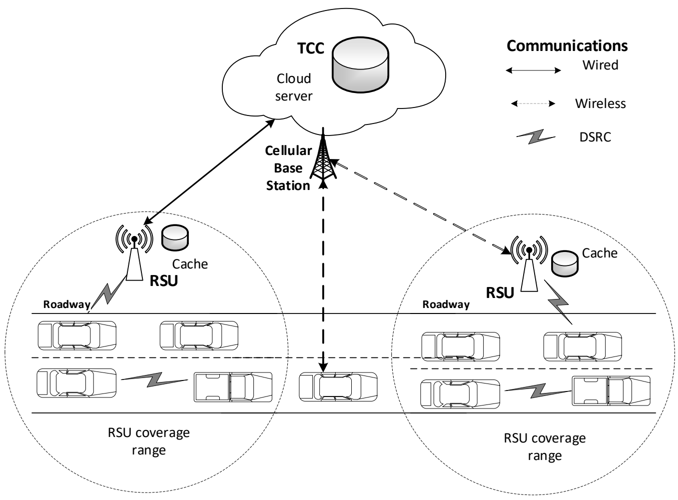


Figure 6.14 RATM-FL System Architecture

Further, we integrate FL methodology to upgrade the learning model between local and global traffic databases. Here, TCC acts as an associate and each RSU is the contributor in the FL framework. Since LSTM is effective in dealing with sequential data; we choose its extended version BiD-LSTM to utilize on RSU [223]. An outline of local LSTM framework is described in figure 6.15. In BiD-LSTM multiple LSTM layer in merged where output from last layer use as the input to the next layer and the scenario continues up to the last layer. Forward-directed and backward-directed layer are worked together so that they can catch both forward and backward attributes of traffic data. In figure 6.15, BiD-LSTM model is shown. RSUs collects traffic information like traffic density, fuel consumption and CO_2 emission of its coverage region from vehicles in real-time. Both the historical data and real-time data are used to train the local model.

TCC collect local updates from RSUs in a predetermined timeline and aggregates the weighted values of the data transmitted by RSUs. Furthermore, TCC evaluates the total weight of the region by using the prediction model output of RSUs and the real-time local and global traffic data gathered from RSU and vehicles. This approach improves the overall traffic network throughput and suggests optimal route for vehicles. TCC cannot wait for enormous time duration, as it will increase the training time that cannot be affordable in a delay sensitive network like transportation systems.

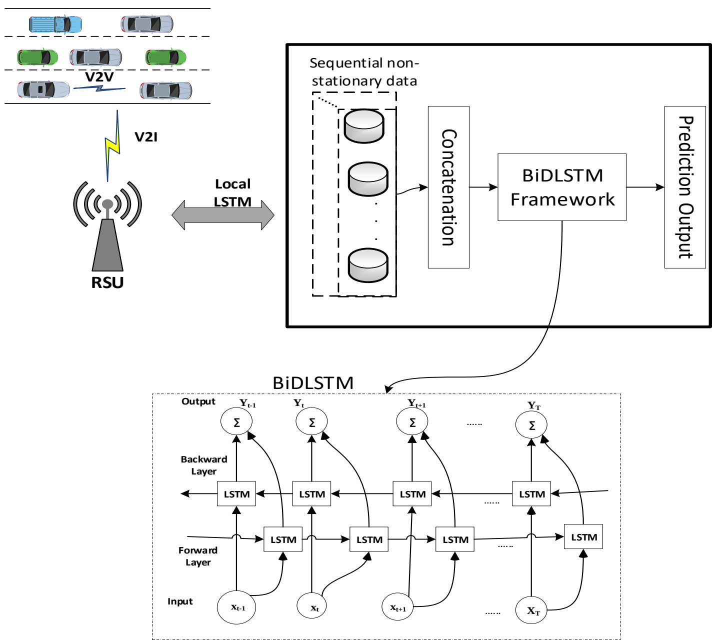


Figure 6.15 Local prediction model at RSU

As per the conventional FL framework, if all the RSUs transmit the trained model to TCC and receive updates from TCC at every iteration, the communication cost and resource requirements increase tremendously. Practically some of the RSUs may be unavailable due to poor connectivity. Additionally, making all of them participate in the model update scenario is redundant if their traffic density is below the threshold. TCC periodically observes the number of vehicles connected with a particular RSU. So, if any particular RSU coverage area is not congested enough, TCC will ignore them for that particular round and proceed with further processing for global model distribution.

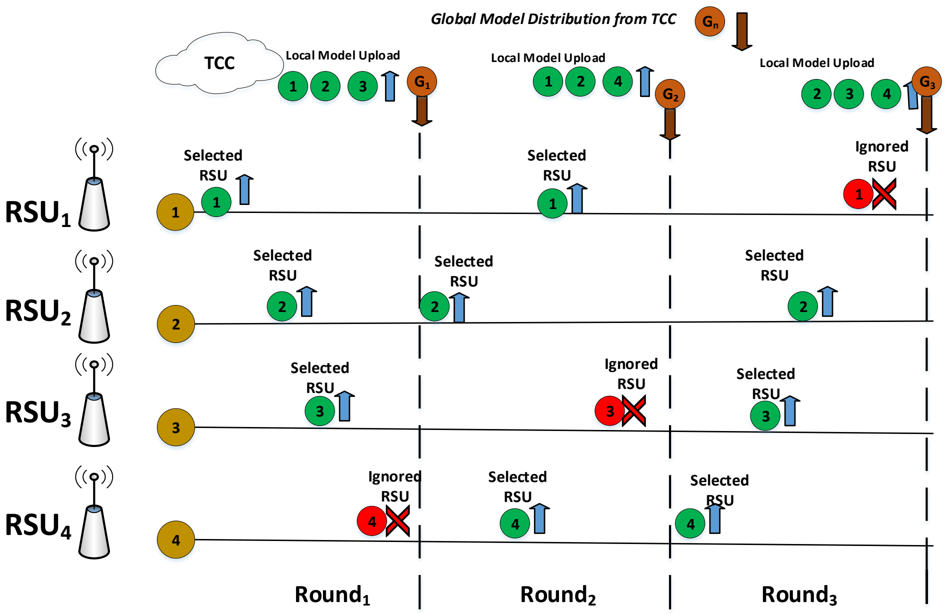


Figure 6.16 RSU selection for FL framework

Let there are total $\mathbb{K} = \{1,2,3, \dots K\}$ number of RSUs where $\mathbb{K}' = \{1,2, .. K_s\}$ is the number of selected RSUs where $\mathbb{K}' \in \mathbb{K}$ ($\mathbb{K}' \leq \mathbb{K}$). In Figure 6,16, the roadmap of RATM-FL is depicted where four RSUs are visible and intend to upload their local model updates to TCC which is shown by the upwards arrow. TCC selects the most significant RSUs in terms of the maximum amount of vehicles they have associated to update the global model and distribute the global updates to RSUs which is shown by the downwards arrow. In round 1, RSU_1, RSU_2, RSU_3 are selected whereas RSU_4 will be ignored by TCC. TCC further distributes the global updates to RSUs which is shown by downwards arrow in Figure 3 (i.e. G_1, G_2, G_3 in the figure).

B. Methodology

In this section, the methodology of the proposed holistic approach is demonstrated where vehicles, roadside, and cloud infrastructure perform the traffic management operation cooperatively. In Algorithm 6.2, each vehicle transmits its information to the nearest RSU. In line 2, if RSU to vehicle connection establishment status is true then each vehicle in its coverage area sends the information tuple containing speed, position, vehicle type, source, destination and lane ID $\{s_i, pos_i, vtype, s, , laneId\}$to RSU in line 4. Further functionality is run by the RSU and TCC that is described in algorithms 6.3 and 6.4 respectively. Generating optimal predicted path for vehicles can be obtained by both RSUs and TCC. In Algorithm 6.3, RSUs are deployed in the crucial intersections. Firstly, in lines 1 to 3 it creates transportation network as connected graph then gathers traffic data from its covered region. Then it processes the data and converts it in normalized form. Deep neural network architecture predicts CDS of its covered roadways and sends model weights to centralized TCC (lines 4-7). When congestion crosses threshold level in line 8, route-planning process for vehicles initiates from line 9 and continues to line 21. RSU explores the destination of vehicle is within its coverage region or not in line 13. When vehicle destination is outside the RSU coverage then TCC handles the route planning operation according to the predicted global traffic model. Conversely, if the vehicle destination falls within the RSU coverage area then for every vehicles k number of shortest path is obtained by K-shortest path algorithm (lines 14-17). Algorithm 6.4 illustrates traffic congestion control by TCC. In the beginning, TCC generates network graph from the transportation map. After that, it obtains the RSU list with their locations and determines which roadways are not covered by RSUs (lines 1 and 2). Each RSU and vehicle can be distinguished by its individual IDs. Then TCC builds the global traffic prediction model from the information fetched from RSUs and vehicles (lines 3-7). Weights of the roadways are updated in a periodic manner. When vehicle destination is not in the range of RSUs, it plans optimal route for them by K shortest path mechanism (lines 8-20). As vehicular network is prone to link failure when vehicle and RSU connection is not established properly, TCC plans the optimal route for vehicles.

Algorithm 6.2: Transmitting information to RSU

Input: Set of vehicles $[v_1, v_2, \dots, v_N]$, Set of RSUs $[R_1, R_2, \dots, R_K]$, $T(I, P)$
Output: Update traffic data

1. $v_i$receives beacon$\{R_i, pos_i\}$ from R_i
2. **While** *ArrivingVehicle()* = true then
3. **for**$v_i = 1$ to N**do**
4. send $\{s_i, pos_i, vtype, s, d, laneId\}$to R_i
5. Receive ACK from R_i
6. end **for**
7. **end while**

Algorithm 6.3: Local Traffic Control by RSU

Input: $T(I, P)$

Output: Optimal route for vehicles

For epoch $(1, r_{max})$ do
Fetch traffic information from T & process the data
Normalize $w_{local}^{RSU} = \{CDS_i^1, CDS_i^2, \dots CDS_i^N\ ,\ CDS_i^N\ \in (0,1)\}$
Foreach RSU_i **do**
Foreach $e_i \in$ E **do**
  Predict CDS for all roads using BiLSTM neural framework
  Send aggregated weight w^l to TCC
  Find congested roads P_{con} with $CDS > \mu$
  Foreach $P_{con} \in$ M **do**
    Foreach $v_i \in$ V do
      Get $Src, Dest\_pair(v_i)$ {get the SD pair for this vehicle}
      Get Present.Location$(v_i) \rightarrow L_{v_i}$
      If $Dest \in$ $\mathrm{Cov_{RSU}}$
        If $L_{v_i} \neq Dest$
          KShP ←getKshortestPath(v_i)
          Set new route for v_i
        End if
      Else
          Send request to TCC
      End if
    End for
  End For
End for
End for

Algorithm 6.4: Traffic Control by TCC

Input: $T(I, P)$,

Output: Optimal route for vehicles

Get $RSU\ list\ with\ locations = \{RSU_1,\ RSU_2, \dots, RSU_K\}$
Get Roadways not covered by RSUs $\{RD_1, RD_2, \dots, RD_N\}$
Gather traffic information from RSUs & vehicles
For epoch $(1, r_{max})$ do
Receive local weights from RSUs
Build global model w^G
Broadcast global model to all RSUs
If RD_i is not in $\mathrm{Cov_{RSU}}$
  Predict congested roads RD_{con} with global model
  Foreach $RD_{con} \in$ M **do**
    Foreach $v_i \in$ V do
      Get $Src, Dest\_pair(v_i)$ {get the SD pair for this vehicle}
      Obtain Present.Location$(v_i) \rightarrow L_{v_i}$
      If $(L_{v_i} \neq Dest)$
        KShP ←getKshortestPath(v_i)

16. Set new route for v_i
17. **End if**
18. **End for**
19. **End For**
20. **End If**
21. **Else**
22. Vehicles check connection status with RSU_i
23. **If** true **then**
24. RSU_i set optimal path for v_i
25. **Else**
26. Repeat steps 11 to 18
27. **End if**
28. **End for**

6.3.2 Mathematical Modelling

This work targets achieving the best route in terms of reduced travel time, fuel consumption, and carbon emissions by building a learning model based on historical and real-time traffic data. This section provides a detailed explanation of the mathematical formulation used to set up the fitness function used to assign the weight of each road in the transportation network.

To ensure efficient route planning of an urban area it is modelled as weighted graph $T(I, E, CDS)$ where $I = (I_1, I_2, \dots, I_N)$ is the set of intersections and $E = (e_1, e_2, \dots, e_N)$ is the set of connecting edges and CDS is defined as the decisive weight of each edge in a particular time frame. A vehicular trajectory path is formed by connecting the source vertex src to destination vertex $dest$ which is denoted by $P(src, dest)_m = (src \rightarrow I_i \rightarrow I_{i+1} \rightarrow .. dest)$ where $(src, dest \in I)$. Suppose there are m number of different trajectories are available to travel from source to destination then trajectory set is defined by $\phi = (P(src, dest)_1, P(src, dest)_2, \dots, P(src, dest)_m)$. As traffic moves in the incoming and outgoing direction of P_{12} is not similar to P_{21} whereas length of both the paths are same.

A. Metrics used to decide traffic status

This part explains the metrics used in our model to build the CDS of each edge. In RATM-FL, total weight of the road is decided based on the following metrics a. traffic density b. speed c. acceleration d. travel time. Every metric is converted to its normalized value so that it falls into the range between 0 and 1. In dense urban vehicular environments, traffic situation is affected due to vehicle platoons' behavior so it is obvious to consider the mean traffic parameters of a road rather than each vehicle's parameters individually.

Capacity of a road $C(p)$ depends on the factors like length of the edge len_{ij} and the number of lanes L_N on the particular edge. In practical scenario length of the vehicles L_{veh_i} and gaps between the vehicles s_{gap_i} are not equal. To formulate the mathematical model these two factors are assumed same for all the vehicles.

$$C(p) = \left\lceil \frac{len_{ij}}{L_{veh}+S_{gap}} \right\rceil \times L_N \tag{6.5}$$

Here, capacity is used as round up function. Traffic congestion induces when number of vehicles on edges are more than the capacity of the edges. If there are Veh_{e_i} number of vehicles present on edge e_i at time t then vehicular density indicator VD_{e_i} of edge e_i is

$$VD_{e_i} = \frac{Veh_{e_i}(t)}{C(p)} \tag{6.6}$$

Next, considered parameters is mean deviated average traffic speed from the benchmark speed of the roadway. Average speed is decided by the mean value of the vehicle's instantaneous speed. For a time duration t average speed of a vehicle is $\overline{s_t}$. If there are n number of sample values are present then average speed of a particular vehicle at time t will be $\overline{s_t} = \frac{s_1+s_2\ldots+s_n}{n}$. If there are m number of vehicles are present on a road at time t then for average speed calculation of a particular road is determined by considering each vehicles' speed which is $\overline{s_{t_{e_i}}} = \frac{\sum_{Veh_{e_i}=0}^{m} \overline{s_t}}{m}$. Speed indicator SD_{e_i} of a particular road e_i is obtained by

$$SD_{e_i} = \frac{s_{max_{e_i}} - s_{t_{e_i}}}{s_{max_{e_i}}} \tag{6.7}$$

Where $s_{max_{e_i}}$ is the maximum allowed speed of the road e_i. As speed and vehicular density indicator consideration is not enough to assign road weight. Acceleration or negative acceleration means deceleration is the further crucial parameter to model road condition. When congestion threshold is low, vehicles can move smoothly in the road. Scenario changes when vehicular density exceeds to the threshold value. Frequent start-stop, acceleration-deceleration and gear change increase the vehicular engine's fuel consumption and CO_2 emission. Therefore, it is necessary to include this parameter in road weight assignment. Normalized average acceleration index AD_{e_i} of road e_i at particular timeframe is calculated by the following equation where $a_{max_{e_i}}$ is the maximum value of acceleration of that road.

$$AD_{e_i} = \begin{cases} \frac{a_{max_{e_i}} - a_{t_{e_i}}}{a_{max_{e_i}}} & a_{t_{e_i}} > 0 \\ 0 & a_{t_{e_i}} = 0 \\ \left| \frac{a_{t_{e_i}}}{a_{max_{e_i}}} \right| & a_{t_{e_i}} < 0 \end{cases} \tag{6.8}$$

Final decisive parameter is travel time, which is very important to build the model, as all the parameters are very much dependent on each other. Each parameters deteriorate due to the heavy traffic load, continuous friction of roads with vehicles and adverse weather impacts that rises fuel consumption and CO_2 emission excessively. Nowadays, traffic detectors, sensors, and cameras always monitor road parameters whereas for simulation environment SUMO has the provisions to place them on experimental road network. Traffic congestion results from the platoon of vehicles' behavior so cluster of vehicles' parameters are more impactful rather than the single vehicle's data. Normalized average travel time indicator TT_{e_i} of edge e_i is formulated as equation 6.9 where $TT_{ff_{e_i}}$ is the ideal travel time of the road and $TT_{t_{e_i}}$ represents the average travel time of vehicles at time t. $TT_{ff_{e_i}}$is calculated based on the free flow speed of the road e_i.

$$TT_{e_i} = \frac{TT_{ff_{e_i}} - TT_{t_{e_i}}}{TT_{ff_{e_i}}} \tag{6.9}$$

$$TT_{ff_{e_i}} = \frac{len_{ij}}{s_{max_{e_i}}} \tag{6.10}$$

According to equations (6.6), (6.7), (6.8), (6.11) CDS of the road e_i will be

$$CDS_{e_i}(t) = \begin{bmatrix} w_1 & w_2 & w_3 & w_4 \end{bmatrix} \begin{bmatrix} VD_{e_i} \\ SD_{e_i} \\ AD_{e_i} \\ TT_{e_i} \end{bmatrix} \tag{6.11}$$

Where $\sum_{i=1}^{4} w_i = 1$, $w_i \in (0,1)$. $CDS_{e_i}(t)$ is observed for each road and will be considered as congested if the value exceeds the threshold limit μ. RSU coverage area congestion indicator ($ACI_{t_x}^{RSU_i}$) is determined by the following matrix where there are N number of roads within its coverage area.

$$ACI_{t_x}^{RSU_i} = \begin{bmatrix} CDS_{t-x}^{e_1} & \cdots & CDS_{t-x}^{e_N} \\ \vdots & \ddots & \vdots \\ CDS_{t-1}^{e_1} & \cdots & CDS_{t-1}^{e_N} \end{bmatrix} \tag{6.12}$$

In the following phase, traffic is predicted based on extended version of LSTM model.

B. Traffic prediction based on LSTM

Sequential traffic data of N segments from the current timestamp t is represented as $CDS_{t_x}^{N}$. Each element of the matrix denotes cumulative decisive score (CDS) of n^{th} road at t_x^{th} timestamp. CDS is decided based on traffic density indicator, speed indicator, acceleration indicator, and travel time indicator where all of them are concatenated. However, for range adjustment data is normalized to maintain the range of [0,1]. For traffic forecasting, CDS is used as input and fed into LSTM module. LSTM is used because of its exclusive capability to handle long-term sequence information [224]. Figure 6.17 describes structure of a conventional LSTM module. A memory unit named as cell is embedded into the network that handles long-term data. Cell unit structure includes input, forget, and output gates. Each gate has its functionality. Forget gate accounts long-term memory h_{t-1} (previous cell output) and the input data x_t, keeps the necessary part, and otherwise discards.
The following formula describes the operation

$$f_g^t = \sigma(w_f.[h_{t-1}, x_t] + b_f) \tag{6.13}$$

w_f signifies the weighted metrics, b_f and σ is the bias vector and sigmoid function respectively. Memory gate targets to trace what new information should be reserved in a cell state. Memory gate has two units one portion is the sigmoid part that finds the values that are required to be upgraded; and other one is $\tan h$ part. Second part produce a new candidate value vector that becomes candidate memory. This method is expressed in following equations. Here, w_i and b_i is the weight metrics and bias vector respectively.

$$i_g^t = \sigma(w_i.[h_{t-1}, x_t] + b_i) \tag{6.14}$$

$$\widetilde{C_t} = \tan h\,(w_C.[h_{t-1}, x_t] + b_C) \tag{6.15}$$

In this point previous cell state C_{t-1} is changed to achieve the value of C_t.

$$C_t = f_g^t * C_{t-1} + i_g^t * \widetilde{C_t} \tag{6.16}$$

At the end, the output of LSTM is decided by the state of the cell. Sigmoid function determines which part of the cell state will be the output and further it goes through the $\tan h$ layer. Two of them are multiplied to achieve the final output.

$$o_g^t = \sigma(w_o.[h_{t-1}, x_t] + b_o) \tag{6.17}$$

$$h_t = o_g^t * \tan h\,(C_t) \tag{6.18}$$

Although one single LSTM unit is capable to predict still to enhance accuracy, we have opted for enhanced version that is stacked bidirectional LSTM [225]. More than one LSTM unit is gathered together where output of non-last layers act as input to the following layer. Two layers analyze the input data sequences. One layer operates in forward direction and another one chooses the backward direction to consider both forward and backward impacts of traffic data. Detail diagram of Stacked Bidirectional LSTM is shown in Figure 6.15.

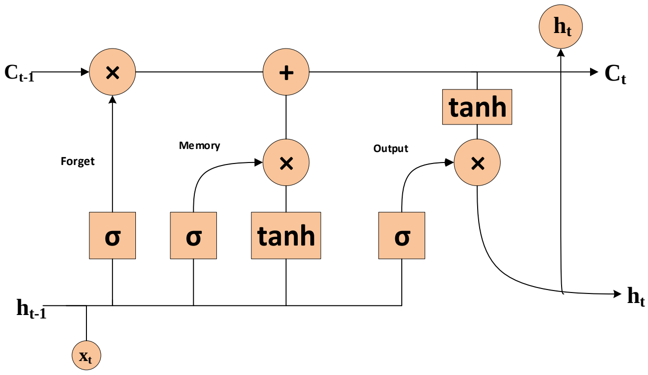


Figure 6.17 LSTM Cell

Each RSU processes the congestion of its coverage area and forward the weighted parameter of the model to TCC. Each RSU obtains the model is denoted as local model w^l which is then processed by TCC and it builds global model w^G. This collaborative machine-learning framework is opted to cover and manage the larger region.

C. Global Model Formation

At each epoch, TCC obtains local models w^l from distributed modules and aggregates their weights after each iteration to build a global model w^G and broadcasts to the participating distributed modules. We have local datasets from each RSUs $\{X^j, Y^j\}^K$ where there are K number of RSUs. TCC can communicate with each RSUs where each RSU is a participator and TCC is the aggregator. Unlike, centralized ML (machine learning) where local data is used for model training in this collaborative approach, whole dataset is not shared by the local RSU. In order to gather distributed model updates TCC uses FedAvg algorithm [226] [227]. In each training epoch r, TCC sends global model w^G to K number of participants. Each RSU uses n_k size of local data whereas $N = \sum_k n_k$. Stochastic gradient descent is used by each RSU to calculate average gradient a_k with learning rate η. Local model is updated by $w_{r+1}^l \leftarrow w_r^l - \eta a_k$. Afterwards, the updated model w_r^l is sent to the TCC. Furthermore, TCC generates global model using the following equation

$$w_{r+1}^{G} = \sum_{k=0}^{K} \frac{n_k}{N} w_{r+1}^{l} \quad (6.19)$$

To train the global model all participating RSUs have to initiate the following optimization problem of the loss function

$$\arg\min_{w\in\mathbb{R}} G_k(w)\,, where\ G_k(w) = \frac{1}{n_k}\sum_{i\in \mathrm{L}_k} g_i(w) \quad (6.20)$$

Here, L_k is the local dataset, n_k is the size of L_k. w is the weight parameter of the local model. $g_i(w)$ is the loss function of sample i so $G_k(w)$ is the average loss function of the local dataset [227]. This training process continues until the model converges which is updated by the TCC to all participating RSUs. Table 6.3 displays all the notations used in this paper.

D. Optimization Problem for a RSU selection

Generally, the participant selection for FL learning from one iteration to another follows random sampling. Without considering the traffic condition, this random selection approach may leads the inclusion of insignificant RSUs which increases communication overhead and energy consumption. Participant RSU selection based on diversified traffic densities enhances network performance in terms of network latency and energy efficiency. The problem is designed as an integer linear programing where each RSU has energy cost $\{E_i(t)\}_{i=1}^{K}$ which is the required energy for each RSUs for the time slot t for computation and communication. Every RSU has a profit of $\{V_i(t)\}_{i=1}^{K}$ at time slot t, which is the number of vehicles, are associated in their coverage area. This indicates that the more vehicles it served in that particular time the profit is more for them. The target is to choose an appropriate subset RSUs at each slot so that the maximum system utility will be achieved. System utility is derived from the difference between profit and the energy spent by the total participating RSUs. TCC can dynamically select the most influential RSUs and ignore the lesser important RSUs at each time slot to provide cost efficient solutions.

$$\text{maximize}[a_1 \sum_{i\in K} \alpha_i(t) V_i(t) - a_2 \sum_{i\in K} \beta_i(t) E_i(t)]\,, \forall t \quad (6.19)$$

Subject to,

$$V_i(t) \leq V_i^{max}(t)$$

$$t \geq t_s + t_u + t_d + t_{agg} \forall K_s \in K$$

$$\alpha_i(t) \in \{0,1\}, i \in K\ \forall t$$

$$\beta_i(t) \in \{0,1\}, i \in K\ \forall t$$

Here, the objective is to maximize the client participants where a_1 and a_2 are the weighting factors. As TCC is more concerned about profit rather than energy consumption a_1 is greater than a_2. $\alpha_i(t)$ and $\beta_i(t)$ is the binary variables. If $\alpha_i(t)$ =1 then RSU is connected to TCC and if $\beta_i(t)$=1 then RSU is in active state to perform the training. $t$is the time duration of each round where t_s is the client selection time. $t_u$and$t_d$is the upload and update time respectively. $t_{agg}$is the time required for aggregation. (t_{agg}, t_u, t_d, $t_s \in \mathbb{R}$) where $\mathbb{R}$ is the set of non-negative real numbers.

Table 6.3. Notations

Symbol	Description	Symbol	Description
$I = (I_1, I_2, \dots, I_N)$	Set of intersections	SD_{e_i}	Speed indicator
$E = (e_1, e_2, \dots, e_N)$	Set of edges	$s_{max_{e_i}}$	Maximum allowed speed
$R_1, R_2, \dots, R_K$	Set of RSUs	AD_{e_i}	Acceleration index
$v_1, v_2, \dots, v_N$	Set of vehicles	$a_{max_{e_i}}$	Maximum value of acceleration
CDS	Cumulative decisive score	TT_{e_i}	Travel time indicator
$P(src, dest)_m$	Vehicle trajectory from source src to destination $dest$	$TT_{ff_{e_i}}$	Free flow Travel time
$C(p)$	Road capacity	μ	Congestion threshold
len_{ij}	Edge length	ACI	Area congestion indicator
L_N	Number of lanes	f_g^t	Forget gate of LSTM module
L_{veh}	Vehicles length	i_g^t	Input gate of LSTM module
s_{gap}	Safety gap	o_g^t	Output gate of LSTM module
Veh_{e_i}	Number of vehicles present on road	w^G	Global model
VD_{e_i}	Vehicle density indicator	w^l	Local model
$\overline{s_t}$	Average speed of a vehicle	η	Learning rate
$\overline{s_{t_{e_i}}}$	Average speed of vehicles present on a road		

6.3.3 Results Analysis

1. Simulation Environment

We incorporate open-source traffic simulators SUMO (simulation of urban mobility) and TraCI (Traffic control interface) to implement traffic scenarios for our simulation. SUMO provides a microscopic traffic simulation environment for generating and analyzing the performance of transportation networks.

- TraCI is an application programming interface (API) provided by SUMO that is collaborated with PYTHON [228]. Traffic information obtained from SUMO is used to train the machine-learning algorithm for traffic management whereas TraCI provides communication between external application python and SUMO. In Figure 5, as an experimental instance, we utilize the real-world map of Kolkata to simulate the traffic that is one of India's most crowded urban cities. OSM (Open Street Map) provides the extracted map of the aforementioned city in XML file format [229]. This downloaded file carries all road-related information including their latitude longitude and names.
- We import the map to SUMO by integrating the NETCONVERT tool to create the road network. After getting the road geometry, a mobility file is created using the ACTIVITYGEN package. It also creates origin-destination trips for each vehicle and provides the trips information in the designated trips file in xml format. NETCONVERT, DUAROUTER and ACTIVITYGEN are SUMO inclusive tools.

Table 6.4. Simulation parameters

Parameters	Value
Car Following Model	Krauss
Safety Gap	2.5m
Vehicle Length	5m
Maximum speed	$40\ km/h$
Traffic Light Cycle	90s
Area	$20\ \times 20\ km^2$
DSRC Channel Bandwidth	10 MHz
DSRC Frequency band	5.9 GHz

- Vehicular speed, occupancy, and pollutant information is gathered from SUMO, which is used to generate optimal routes, and assigns to vehicles in SUMO. To calculate CO_2 emission and fuel consumption Handbook Emission Factors for Road Transport V.3 (HBEFA3) based emission model of SUMO is used which is a statistical model for computing fuel consumption and CO2 emission for each time step and vehicles [229]. These two pollutant factors are dependent upon acceleration and vehicular speed.

Simulation parameters are summarized in Table 6.4 whereas simulation time is 3000s. We have taken each vehicle length, as 5m and the gap between the vehicles are 2m to generate the vehicle trajectories in SUMO. Maximum speed at free flow condition is taken as 45Km/h. V2V communication channel bandwidth is 10MHz followed by the DSRC frequency band 5.9 GHz.

2. *Metrics used for performance evaluation*

FL-based framework RATM-FL is compared with the most relevant ITS systems from the literature which are PTPR [234], REFOCUS+ [101], and PRGM [233] to establish the significance of FL in route planning. PTPR is a distributive system where travel time and vehicular density are estimated to balance the traffic load among multiple routes. REFOCUS+ delivers a fog-cloud-enabled route guidance system to encounter traffic congestion. PRGM follows a collaborative involvement of vehicle clusters and cloud platforms to address traffic congestion scenarios. All these specified approaches used for simulation are elaborated in Chapter 2 section 2.4. Results are observed based on the five-performance assessment metrics namely travel time, waiting time, speed, CO_2 emission, and finally fuel consumption [39].

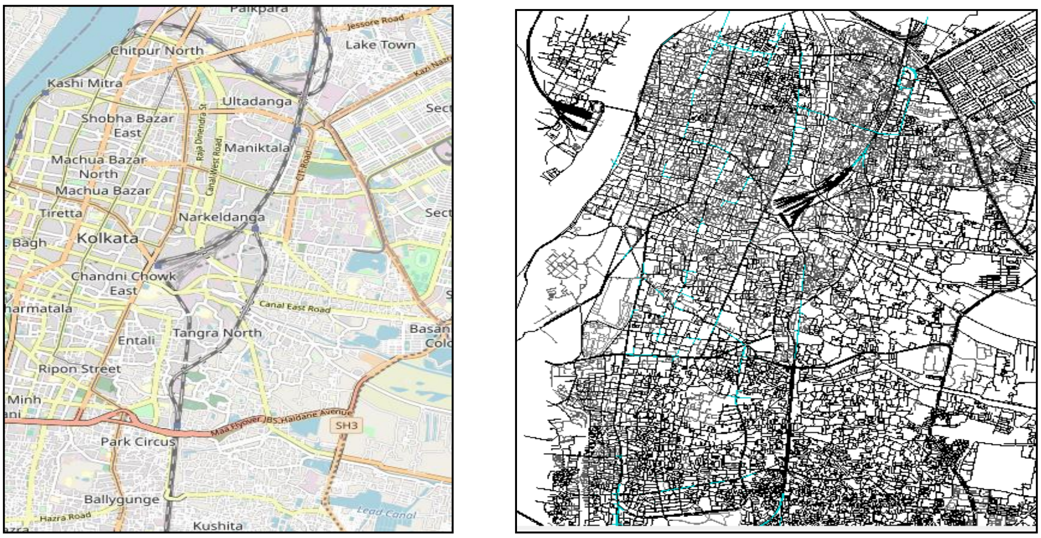


Figure 6.18 OSM map of Kolkata and its imported instance in SUMO

Being a microscopic traffic simulator SUMO delivers individual vehicle dynamics. For overall comparison purposes, mean values of the parameters are taken. Pollutants, waiting time and travel time are linearly increasing with number of vehicles that simultaneously escalate traffic congestion. Average speed of the vehicles is inversely proportional with number of vehicles. Therefore, these factors are considered for performance evaluation of proposed approach.

- Travel time indicates the duration vehicles require covering from origin to destination.

- Waiting time indicates the duration vehicles are stopped in red signal, which is calculated in seconds.
- Average speed of vehicles in road measured in meter per second.
- Average consumed fuel that is measured by millilitre per second.
- Average emitted CO_2 by vehicles, which is measured in gram per second.

Simulation Outcome

The varying number of vehicles for the experimental region performs simulation. Results are observed for PTPR, REFOCUS+, PRGM and the proposed system based on five aforementioned performance metrics. Figure 6.19 illustrates the graph of average CO_2 emission and fuel consumption for varying numbers of vehicles respectively. Next, Figure 6.20 illustrates the graph of average travel time and waiting time for varying numbers of vehicles respectively. Figure 6.21 shows the graph of average vehicular speed with respect to varying number of vehicles.

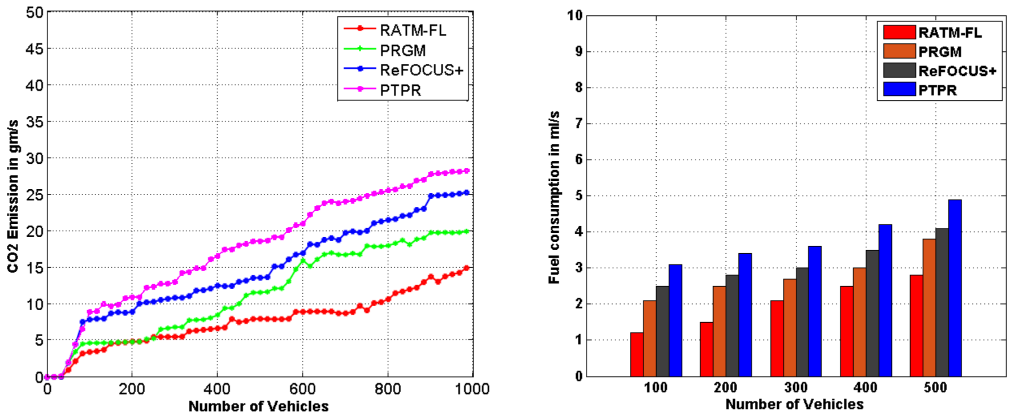


Figure 6.19 Evaluation of RATM-FL in comparison with existing systems with respect to CO_2 emission and Fuel consumption

It can be analyzed from figure 6.19 that average CO_2 emission and fuel consumption is reduced for the proposed system RATM-FL in comparison with PTPR, REFOCUS$^+$, and PRGM. PTPR delivers worst performance among all the considered existing systems as it functions based on the RSU suggested route, which is not optimal for managing the larger region. They opt for the localized shortest path planning based on the vehicular speed and overall time spent on the road by vehicles. For fruitful traffic management, several characteristics should be acknowledged that are road capacity, speed along with acceleration and road condition. Rest of the frameworks adapt hybrid architecture and consider multiple parameters that yield remarkably well performance due to the overall handling and meticulous understanding of traffic characteristics.

This effectively reduces carbon emission and fuel consumption. Congestion control and travel time minimization reduces waiting time and frequent acceleration and deceleration of vehicles. This results in decreased CO2 emission and fuel consumption.

Figure 6.20 exhibits that average travel time and waiting time are reduced for proposed system RATM-FL in comparison with PTPR, REFOCUS$^+$, and PRGM. PTPR encounters congestion and consecutively it affects by the red signal time, which increases its travel time and waiting time. Whereas REFOCUS$^+$ performs better than PTPR due to its incorporation of multi-metric fitness function for road congestion measurement. As it does not consider the traffic light generated congestion, it takes extra travel time and waiting time than PRGM that consequence more pollution generation. Although PRGM predicts traffic flow and congestion status, still RATM-FL has best traffic efficiency since it applies more accurate congestion prediction results for road weight calculation. The cluster dependent communication of PRGM generates extra network overhead that degrades its prediction performance.

Figure 6.21 demonstrates that average vehicular speed is increased for RATM-FL in comparison with PTPR, REFOCUS$^+$, and PRGM. Average vehicular speed decreases from its free flow value when the number of vehicles increases. Further, the overall evaluation metrics are compared with respect to existing schemes in Tables 6.4 and 6.5. Table 6.4 shows total travel time, CO_2 emission and fuel consumption values where the length of the optimal route from the starting point to the destination point is 12.4 Km. Table 6.5 gives the percentage reduction values of RATM-FL concerning PTPR [23], ReFOCUS$^+$[25], and PRGM [26] for travel time, CO_2 emission and fuel consumption.

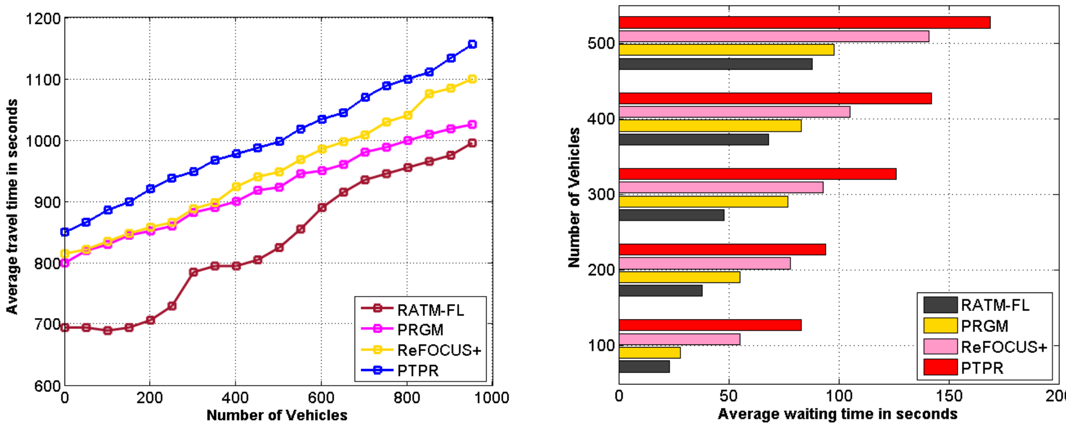


Figure 6.20 Evaluation of RATM-FL in comparison with existing systems a. Travel time b. waiting time

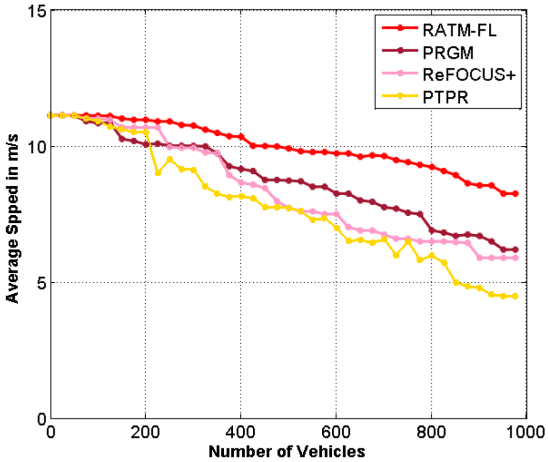


Figure 6.21 Comparison of RATM_FL with existing systems based on average speed vs. number of vehicles

RATM-FL outperforms the PTPR, ReFOCUS^{+}, and PRGM in terms of travel time in Kolkata by 48%, 39.8%, and 14.52% respectively. According to CO_2 emissions and fuel consumptions in Kolkata RATM-FL outperformed the other frameworks; PTPR, ReFOCUS^{+} and PRGM by 42%, 27%, 19.26% and 47%, 33.86%, 23.26% respectively. Thus, RATM-FL can effectively smooth the traffic and minimize congestion in the area.

Table 6.4 Comparison of evaluation metrics based on experimental region

Performance metrics	PTPR	ReFOCUS^{+}	PRGM	Proposed
Travel time (h)	208.45	180.86	126.65	108.25
CO_2 emission (Kg)	450.38	356.75	320.12	258.46
Fuel consumption (liters)	408.38	325.75	280.78	215.45

Table 6.5 Percentage reduction of evaluation metrics based on experimental region

Performance metrics	PTPR	ReFOCUS^{+}	PRGM
Travel time (h)	48	39.8	14.52
CO_2 emission (Kg)	42	27	19.26
Fuel consumption (liters)	47	33.86	23.26

- *Effectiveness of proposed system architecture*

In this subsection, we observe the effectiveness of our hybrid federated learning-based traffic prediction framework from the perspective of accuracy and loss [230]. Since BiD-LSTM is used as a local model, we use the simulated traffic data from the real-time map as input to estimate the congestion status of the roads for the next time frames. We segregate the data training and testing subsets where 80% is used for training and remaining is used for testing.

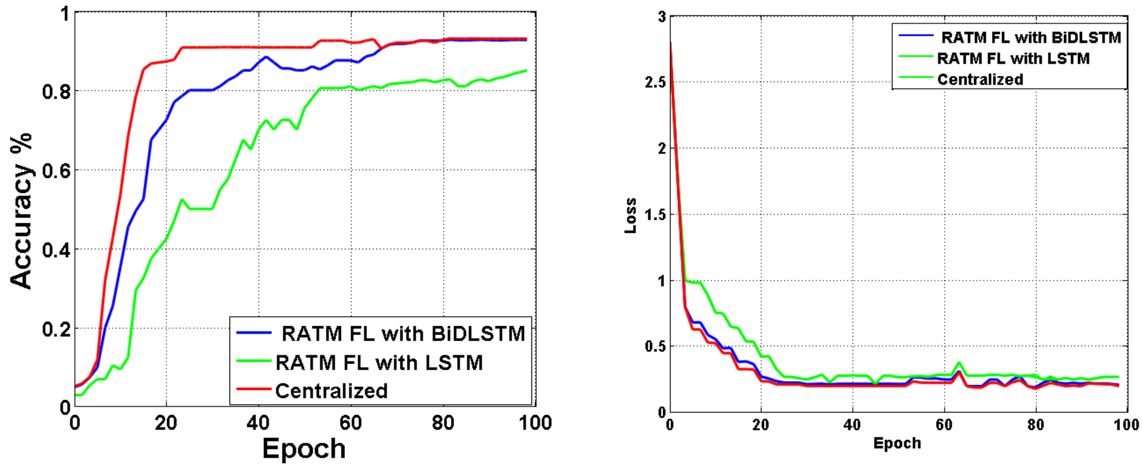


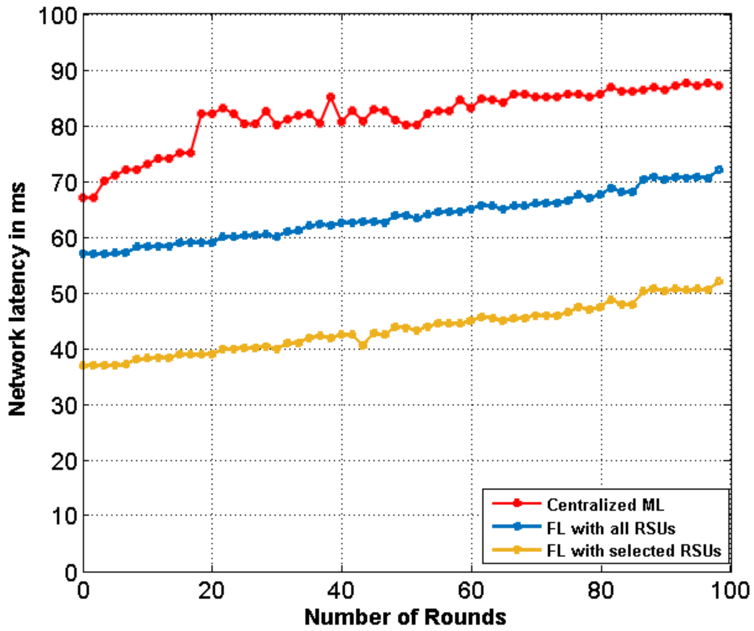
Figure 6.22 Accuracy and loss of RATM-FL

To highlight how the model is performing two main parameters should be considered that are accuracy and mean square error (MSE). MSE is determined by $MSE = \frac{1}{S}\sum_{i=1}^{S}(actual_i - predicted_i)^2$ where S is the number of sample data. On the other hand, accuracy is the percentage of the ratio of error to actual value. Simulation is performed on a system that has 2.2 GHz Intel i7 processor with 16GB of memory. We have incorporated TensorFlow Federated (TFF) 0.4.0 with TensorFlow 1.13.1 back-end. This is an open-source framework for distributive ML algorithm design. In Figure 6.22 accuracy percentage and loss performance of predicted data is shown where we can observe that training with BiD-LSTM provides better accuracy than the conventional LSTM model. The model is trained at a learning rate of 0.001 with 100 number of iterations. Training with RATM-FL ensures higher accuracy percentage that delivers efficient system performances.

In this research, IEEE 802.11p is used as a primary vehicular communication channel, collaborating with cellular-based 5G standard [232]. Network performance is observed by considering latency while exchanging traffic data in Figure 6.23. Table 6.6 illustrates the parameter settings used for simulation [231]. If there are total N number of vehicles and $N - p$ is the number of vehicles are connected with RSU, t is the time slot id then the latency of a RSU area is $Latency_T^{RSU_k}$. At TCC, latency is formulated by $Latency_T^{TCC}$, where p number of vehicles are connected with TCC and $k \in \{1,2,3,..K\}$ is RSU indexes in the transportation network.

$$Latency_T^{RSU_k} = \sum_t^T \sum_n^{N-p} Latency_n^{RSU^k}$$

$$Latency_T^{TCC} = \sum_t^T \sum_k^K Latency_{RSU_k}^{TCC} + \sum_t^T \sum_n^p Latency_n^{TCC}$$



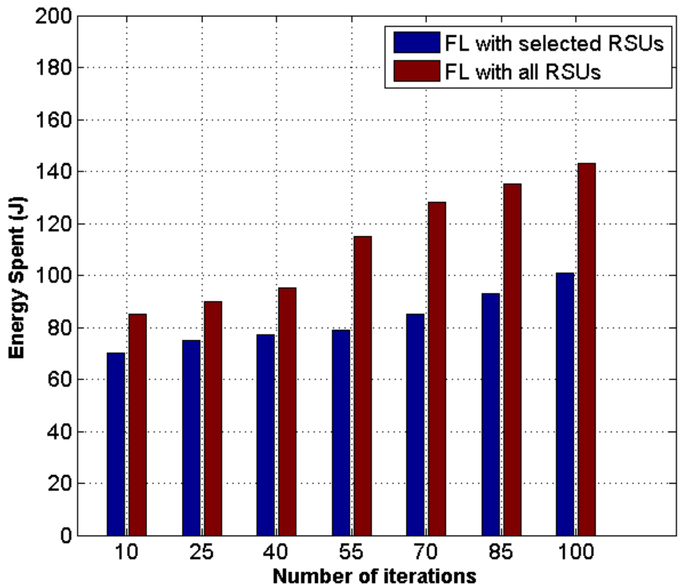


Figure 6.23 Network Latency and Energy consumption comparison of FL framework with all RSUs and selected RSUs

Table 6.6 Parameter settings

Parameters	5G
Data rate	1 to10 Gbps
Channel bandwidth	100 MHz
Frequency	28 GHz
Transmit power	30 dBm

In Figure 6.23, network latency performance is evaluated for centralized machine learning (CML) and conventional FL and RATM-FL with RSU selection. For CML network latency or delay is greater than FL because it has to handle large-scale of data sets. In the case of CML, all the participating RSUs exchange actual traffic data at the training time whereas in FL only the model parameters are transmitted by the RSUs. In each iteration communication overhead is more, which increases the delay for the centralized approach than FL. In the case of a selective RSU-based FL framework delay is minimal because it considers heterogeneity of RSUs which fastens the training time. TCC discards the lesser significant RSUs that make the FL framework more robust and reduces the overall latency of the system. Figure 6.23 also illustrates the comparison between spent energy and number of rounds. In this figure, we compare the proposed selective RSU-based FL scheme RATM-FL with conventional FL. We can observe that RATM-FL outperforms FL in terms of energy consumption, especially for further communication rounds. This is because, in RATM-FL TCC optimally selects RSUs for local transmission according to their significance in the current traffic scenario. As a result, the average energy consumption for RATM-FL is less than conventional FL. In particular, RATM-FL can minimize energy consumption up to 28% compared to conventional FL. Comprehensively, the simulation results in this work exhibit that our proposed system and related algorithms make the transportation management scheme more precise and reduce the occurrence of congestion.

6.4 Chapter Summary

In this chapter, an intelligent re-routing algorithm named Enhanced A*, that ensures reduced carbon emission, fuel consumption and travel time with increased vehicular speed has been proposed. This approach introduces a heuristic cost function to find alternate routes for vehicles that are less congested and feasible. For performance evaluation conventional routing algorithms Dijkstra and A* are considered that confirm the significnce of this approach.

Further, this chapter deduced an intelligent multi-layer route planning system based on RSU-cloud architecture to minimize traffic congestion and pollution emissions and thereby ensure overall transportation efficiency. On one hand, optimally placed RSUs manage traffic in critical areas; while on the other hand, the cloud server oversees the entire region. This efficient RSU selection scheme enhances system performance in terms of network latency. Our proposed methodology for traffic status measurement estimates road conditions and utilizes this information to calculate the most convenient route to the destination. In particular, this paper has introduced an ILP approach that maximizes system utility by strategically selecting RSUs for participation in each FL based iteration, taking into account the variable traffic density. Performance evaluation demonstrates that compared to recent existing route guidance systems, the proposed RATM-FL system maximizes traffic efficiency by minimizing congestion and road emissions. Specifically, in Kolkata, RATM-FL demonstrates superior performance compared to PTPR, ReFOCUS+, and PRGM, reducing travel time by 48%, 39.8%, and 14.52% respectively. Furthermore, in terms of CO_2 emissions and fuel consumption in Kolkata, RATM-FL exceeded other frameworks, including PTPR, ReFOCUS+, and PRGM, reducing emissions by 42%, 27%, 19.26%, and fuel consumption by 47%, 33.86%, and 23.26% respectively. Future research will explore the potential of 5G advanced communications for ultra-low latency data dissemination and incorporate advanced federated learning algorithms to enhance Intelligent Transportation Systems (ITS).

❖ Publications from this chapter

1. Sreya Ghosh, Iti Saha Misra, "Enhanced A* Algorithm to reduce CO2 emission and fuel consumption in Intelligent Transportation Systems", In 2023 International Conference on Communication, Circuits, and Systems (IC3S) 2023 May 26 (pp. 1-6). IEEE.

2. Sreya Ghosh, Iti Saha Misra, Tamal Chakraborty, "RATM-FL: RSU Assisted Traffic Management using Federated Learning for Intelligent Transportation Systems", communicated to Wireless Networks, Springer.

7

Balanced Resource Allocation with Improved Performance for 5G C-V2X Networks

7. Balanced Resource Allocation with Improved Performance for 5G C-V2X Networks

Outline of the Chapter:

7.1 Introduction

"Innovation is the ability to see change as an opportunity, not a threat." —

Steve Jobs

Driven by the rapid enhancement of autonomous driving and next-generation vehicular applications that handle enormous traffic loads along with the requirement of ultra-low latency and high reliability, the vehicle-to-everything (V2X) communication paradigm emerges as the pivotal solution [235]. Conventionally there are two radio standards are allocated for V2X; one is dedicated short-range communication (DSRC) and another one is cellular V2X [236]. It ensures data dissemination among vehicles and other network bodies including edge, backbone servers, and pedestrians. With the advent of advanced fifth-generation (5G) and evolving 6G networks, wide bandwidth and high data rates are provided for C-V2X, which facilitates heterogeneous traffic applications through cooperative awareness among connected automated vehicles (CAVs) and vulnerable road users (VRUs). VURs are prone to accidents which need to be considered by CAVs for safer Cooperative Intelligent Transport Systems (C-ITS) [237]. The C-V2X framework is furnished in 2017 by the Third Generation Partnership Project (3GPP) followed by the 5G proposal to deliver revolutionary data-driven vehicular applications. These amendments are not only related to road safety but also ensure intelligent traffic management [238]. Two transmission modes are designated for C-V2X to deliver communication both within coverage and out of coverage region named mode 3 and mode 4 which is also acknowledged as side link communication [239]. For the first one, radio resources are assigned by LTE base stations centrally through Uu interface. In the case of the later, without the intervention of BS, vehicles are allocated radio resources by themselves following the sensing-based-semi persistence scheduling (SB-SPS) through PC5 interface [240] [241]. SB-SPS handles the periodic exchange of information on physical layer. These information sharing messages are known as cooperative awareness messages (CAM) in Europe which is fixed by ETSI. In the US they are called basic safety messages (BSM) fixed by the Society of Automotive Engineers (SAE) [242]. Vehicles generate CAM so that they can broadcast their updates to adjacent vehicles that establishes the successful implementation of security and safety services. 3GPP endorses SB-SPS schemes to handle these fixed sized and periodic awareness packets.

As mode 3 works in a centralized manner, it has acquired global knowledge about the network and reduced the possibilities of allocating the same resources to vehicles that minimizes the collision probability. Nevertheless, mode 3 is only applicable within cellular coverage, which increases communication overhead and computation expenditure with the increment of vehicular density [243]. On the contrary, mode 4 is lightweight and can operate beyond cellular coverage. Mode 4 is vulnerable to resource conflicts as it operates in a distributive manner. Whenever traffic density and mobility are maximized resource, conflicts arise and result in collision, which generates poor QoS performance. Collision in CAM transmission affects traffic safety because of inappropriate knowledge distribution about adjacent vehicles [244]. Optimal resource scheduling algorithms for C-V2X mode 4 are a major thrust area of research. In SB-SPS, vehicles independently select resources in a particular interval of time. The issue that arises here is that vehicles are unaware of the resources further will be used by the neighboring vehicles. Henceforth, multiple users may select identical resources for broadcasting which generates huge collisions and causes service quality degradation. Vehicles must be aware of the resources picked by adjacent vehicles to avoid such abrupt situations. Machine learning paradigms have enriched several aspects of vehicular domains, which is tremendously favorable for ensuring optimal solutions. *Motivated by these insights, in this chapter, we propose a cluster head vehicle (CHV) assisted Q-learning-based resource allocation (CHQ-RA) approach that encounters packet collisions and CAM losses because of half-duplex scenarios.* In half-duplex circumstances, while vehicles are transmitting CAM it is unable to receive CAM from others in the identical sub-frame [245]. CHV allocates resources in a balanced manner, which improves performance in comparison to the existing selection approaches. This research introduces an innovative approach to resource allocation in vehicular networks, leveraging Cluster Head Vehicles (CHVs) for efficient management.

7.1.1 Contributions of this chapter

The primary contributions of this chapter are:

1. ***Cluster Head Vehicles (CHVs) for Resource Allocation****:* Instead of allowing each vehicle to select resources independently, the CHVs distribute them more efficiently by maintaining cooperative awareness of the environment. The CHVs are chosen based on their stability, determined by factors such as speed, acceleration index, and probability of successful packet delivery.
2. ***Q-learning-based Sensing Window Selection****:* Considering the varying traffic conditions, Q-learning is used to dynamically decide the sensing window for CHVs. This minimizes network delays and overhead, ensuring quicker updates by aligning sensing time with real-time traffic conditions.
3. ***Fitness Function for Vehicle Selection****:* A fitness function is designed to prioritize vehicles that are most suited for resource utilization. This ensures a balanced and efficient allocation of resources among vehicles.
4. ***Simulation Outcome****:* Extensive simulations analysis were conducted for the varying scenarios such as the number of vehicles, Cooperative Awareness Message (CAM) size, and the distance between transmitter and receiver. The proposed approach outperforms existing protocols like traditional mode 4, E-SPS [103], and EB-PRS [104] in terms of the performance evaluation metrics such as Packet Reception Ratio (PRR), Collision Ratio (CR), and Update Delay (UD).

This research delivers a substantial improvement in vehicular communication by optimizing resource distribution and reducing network latency.

7.1.2 Chapter Organization

The rest of the chapter is arranged in this manner. In Section 7.2, the proposed work is described. Section 7.3 defines the result analysis of the proposed CHQ-RA. Subsequently, Section 7.4 concludes this chapter.

7.2 Intelligent sensing-based resource allocation using Q-Learning

In cellular vehicular-to-everything (C-V2X) mode 4, vehicles schedule resources autonomously, defined by semi-persistent scheduling. According to the sensing information obtained in side-link control information (SCI) through the physical side-link control channel (PSCCH), vehicles select the resources for cooperative awareness message (CAM) transmission and preserve resources for further transmissions. Half-duplex problem and allocation of overlapped resources induce packet collisions that degrade overall system performance. In this paper, Cluster Head Vehicle (CHV) assisted balanced resource allocation is proposed entitled as CHQ-RA. CHVs are the most stable vehicles, which is determined by each vehicle's stability index. CHV acts as an agent and incorporates Q-learning-based paradigm to ensure traffic density-based dynamic sensing window allocation. It also disseminates the available resources among cluster member vehicles according to their link stability performance and latency requirements aiming at best exploiting of the available resources. A comprehensive performance evaluation is done in comparison with the prior relevant works to establish the superiority of the CHQ-RA under diverse scenarios in terms of the packet reception ratio (PRR), update delay (UD) and collision ratio (CR). PRR, CR and UD performance are analyzed based on varying traffic density, CAM size and transmitter-receiver distance.

7.2.1 Proposed Work

A. System Model

An urban road scenario is taken as shown in Fig. 1, where $N = \{1,2,2 \ldots n\}$connected and autonomous vehicles (CAVs) are randomly distributed in a roadway. Each CAV has adequate computing capability and shares the same pool of resources. They broadcast CAMs by using radio resources using the PC5 interface. As depicted in Figure 7.2, resources are orchestrated over frequency and time domain whereas the frequency domain is split into sub-channels and the time domain is split into sub-frames. Vehicles form a platoon and the most stable vehicle from the platoon is elected as platoon leader or cluster head. Each vehicle is enabled with GPS and other traffic sensors to obtain its status regarding location, velocity, acceleration, etc. In Figure 7.1, platoon leader vehicle 'A' detects vehicle 'M' whereas it cannot detect vehicle 'B' because of the obstruction by vehicle 'M'. Through the V2V communication with vehicle M vehicle L can easily receive the information about vehicle B. In this way, platoon leader vehicle can be aware of its neighbouring environment and channel state information of all the vehicles in its platoon through the mm-wave link. This will reduce the network delay and overhead. Leader vehicle gathers traffic data and broadcasts it for all the recipients within its communication radius.

C-V2X works in 5.9 GHz frequency band and allocates 10 and 20 MHz channels. According to the depiction of Figure 7.2, the channel is segregated into sub-frames in the time domain whereas in the frequency domain sub-frames contain multiple sub-channels. The size of the sub-channel is not fixed which is dependent upon the number of resource blocks (RB) they hold. Sub-channel is arranged in such a manner in C-V2X where physical side-link shared channels (PSSCH) represent the transport blocks (TB) and physical side-link control channels (PSCCH) consist of side-link control information [246]. As per SPS, vehicles retain specific RBs with a transmission frequency-based RC that is reduced by one afterward. When a vehicle wants to select fresh resources then it has to curtain off the available candidate single-sub-frame resources (CSRs) in the selection window [247] [248].

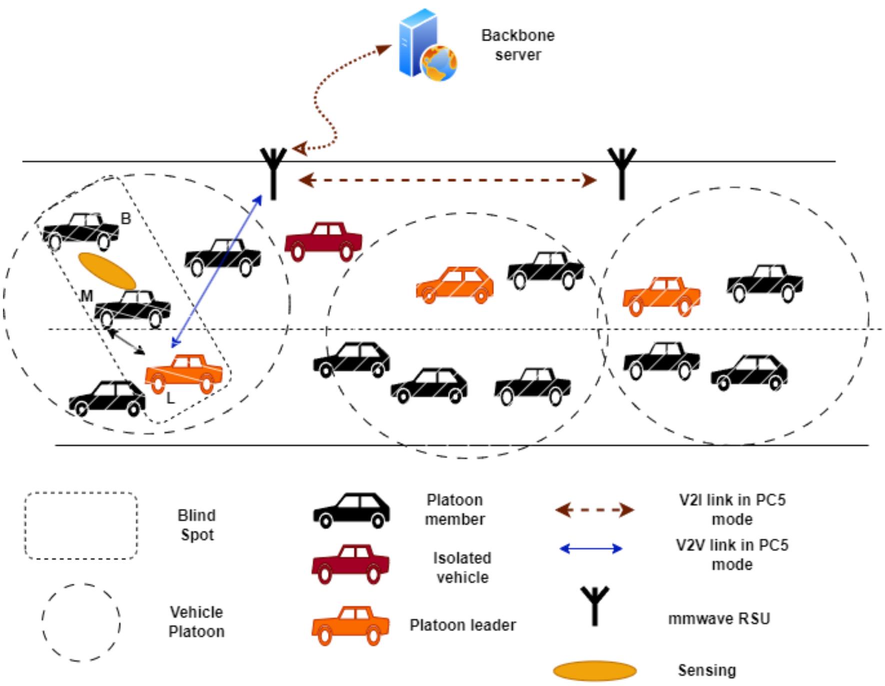


Figure 7.1 System Architecture

Vehicles acquire SCI information in the sensing window and the CSRs reserved by other vehicles are ruled out. The average reference signal received power (RSRP) along with the received signal strength indicator (RSSI) of RBs are constantly scrutinized within the sensing window. The available CSR with an average RSRP that is greater than the threshold value is blocked [249]. The SPS model utilizes random RCs to scatter the available resource lists (ARL) of vehicles. After the guidance of selection of non-overlapping resources, still it is unavoidable to coincide the resources among them due to highly dense environment. Therefore, the random selection of RCs are not an optimal solution and leading to packet collisions.

Paramount importance should be given in choosing proper CSR from the available ARL to enhance the transmission utility of CAM broadcast [250].

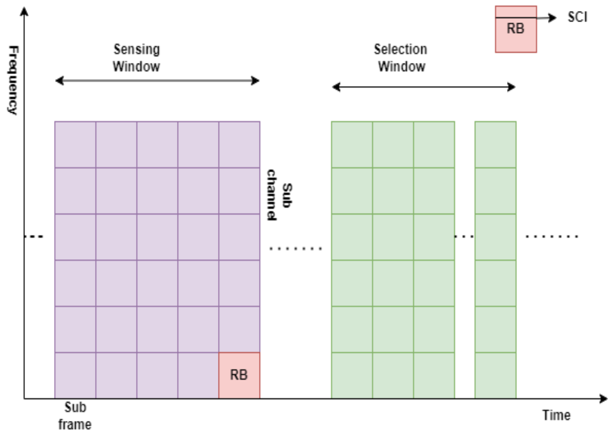


Figure 7.2 Illustration of resource block orchestration

B. Methodology

In conventional SB-SPS mode 4, vehicles sense available resources and then accordingly each of them randomly selects resources for CAM transmission. This generated degraded performance especially in dense traffic scenarios due to autonomous resource allocation without the knowing the allocated resources by other vehicles. When a particular vehicle transmits CAM in a sub-frame, it cannot obtain CAM from other vehicles. This scenario is termed a half-duplex problem, increasing the collision probability in vehicular communication.

i. Stable vehicle identification for platoon leader selection

For cluster-head vehicle selection from a platoon, the proposed model considers several factors, including stability index and QoS value. A vehicle's Stability index depends upon the vehicle's relative speed and acceleration to all its neighbouring vehicles. Here, s_i is the speed of the vehicle and N_i is the set of vehicles and its neighboring vehicles. $avg_x$and max_x are the average and maximum speeds respectively of the vehicle platoon. Higher the value of SI_i denotes higher stability.

$$SI_i = 1 - \frac{\left| |s_i| - avg_{x \in N_i} |v_x| \right|}{max_{x \in N_i} |v_x|} \tag{7.1}$$

Further considered metrics for cluster head selection is acceleration index AI_i. Only velocity consideration is not enough for measuring the stability of a vehicle. Acceleration index calculation is required for vehicular mobility management. a_i is the acceleration. $avg_y$and max_y are the average and maximum acceleration respectively of the vehicle platoon.

$$AI_i = 1 - \frac{\left||a_i| - avg_{y \in N_i}|a_{x=y}|\right|}{max_{y \in N_i}|a_y|} \tag{7.2}$$

P_{pkt} is the successful packet receiving probability which is defined as the ratio of packets received P_R^v by the 1-hop neighbor vehicles to packets sent P_S^v by the particular vehicle.

$$P_{pkt} = \frac{P_R^v}{P_S^v} \tag{7.3}$$

$$CH_{veh} = W_1 \times SI_i + W_2 \times AI_i + W_3 \times P_{pkt} \tag{7.4}$$

$$\sum_{i=1}^{n} W_i = 1 \tag{7.5}$$

According to equations (1) (2) and, (3) $CH_{veh}$is observed for each vehicle. By considering the relative significance of each metric and each vehicle, the highest scored vehicle is selected for CH. Moreover, backup vehicle set are also computed based on the rank for CH failure. The backup CHs start functioning whenever the present CH fails to perform. This makes sure the vehicles can communicate among themselves. Algorithm 7.1 for the cluster-head (CH) vehicle selection works as follows. Firstly, each vehicle broadcasts its velocity and acceleration index 1-hop away. Then each vehicle computes its QoS index value and broadcasts that to its adjacent vehicles. Vehicles elect CH based on highest stability index and QoS value. CH broadcasts acknowledgement to its neighbours.

Algorithm 7.1: Cluster head vehicle selection

```
For v_i in ℕ do
    Broadcast beacon messages to neighbor vehicles
    Analyze stability index and QoS
    Broadcast to 1-hop neighbors
End For
For v_i in ℕ
    Elect vehicle with maximum stability index and QoS
    Broadcast the CH_veh selection msg
    Others send join request
    Send ACK to 1-hop neighbors
End For
```

ii. Q-learning based Sensing time selection

Unlike conventional SPS where vehicles select resources from available list without any policy, in CHQ-RA resources are intelligently allocated to each vehicle based on Q-learning techniques. With a predefined sensing window, size of 1 sec that includes 1000 sub-frames and 1000 slots generally identified as long-term sensing which instigates unavoidable delay in resource allocations. Short term sensing can generate more delay if vehicles cannot identify available resources. For the requirement of ultra-low-latency communication, dynamic sensing time selection can be a potential solution. CHV can set the sensing window size between $0.1s\ to\ 1s$ according to the present traffic conditions. In CHQ-RA, each cluster head vehicle acts as agents that gains knowledge from transportation environment and applies it to allocate resources optimally. We split total time T into multiple similar time slots t. Two types of actions are taken for resource sensing procedure one is large-scale sensing and another one is small-scale sensing. The states of the environment are noticed by the CHV and in every time slot, RBs are allocated to a particular vehicle depending on its latency and reliability performance. In Q-learning, an agent acquires the knowledge of taking optimal decisions by observing the environment [251] [252]. Agent notices the state space $s \in S$ and choose appropriate actions from action space $a \in A$. It obtains a reward $r(s, a)$ for its chosen action and proceeds to the further state $s_n = s(t+1) \in S$. Reward function guides the agent about the future actions. CHV looks traffic density VD_t, $RSSI$, the delay occurred for the generated packetD_t. CHV selects an action from action set $\{ A \in T_{sensing_i} \in (0.1,1)sec\}$ based on present condition. Reward function is designed as the function of the total number of V2V link capacities C and maximum predefined delay D_0 and present delay D_t. α_i is the weighting factor.

$$r(t) = \alpha_1 \sum_{i=1}^{N} C - \alpha_2 (D_0 - D_t) \tag{7.6}$$

CHV selects the action depending on the Q values. The Q values of the tuple (s_t, a_t) of policy p is $Q(s_t, a_t)$ which is determined by the reward so that $\acute{a} \in A$ can be executed. Then the policy p is defined as $a_t = arg\max_{a \in A} Q(s_t, a)$. However, the Q value is changed as follows

$$Q_{t+1}(s_t, a_t) = Q(s_t, a_t) + \tau\{r(t) + \gamma \max_{s \in S} Q_{t+1}(s_t, a_t) - Q(s_t, a_t)\} \tag{7.7}$$

Algorithm 7.2: Q-learning based sensing time allocation

1. Initialize experience replay memory $\mathcal{M}$
2. Initialize Q function with random weights δ
3. Initialize target $\acute{Q}$ function with same weight
4. **For** epoch 1 to E_{max} do
5. **For** Time t_1 to t_N do
6. With probability ε, select a random action
7. Elsewise choose $a_t = arg \max_{a \in A} Q(s_t, a)$
8. Follow $T_{sensing_i} as\ a_t$ and observer reward $r(t)$
9. Compute $s(t+1)$
10. Reserve the experience $(s_t, a_t, r(t), s(t+1))$ in $\mathcal{M}$
11. Random mini-batch experiences are sampled from $\mathcal{M}$

12. Upgrade target network parameters to
13. Cache the updated experiences
14. End For
15. End For

Here, τ is the learning rate. The state transitions are updated by using the Markov decision process (MDP). To accumulate the Q values of all the state action pairs is not computationally possible. In deep Q learning, function approximation is done by mapping states to actions rather than storing them. Leaders share the reward functions and consider the actions followed by others. Vehicles use these shared rewards for further capacity improvement. Algorithm 7.2 describes the Q-learning-based sensing time allocation. In the training phase, CHV trains the network and selects $T_{sensing_i}$ according to the policy. CAM is transmitted and CHV notices the reward $r(t)$. Knowledge of $(s_t, a_t, r(t), s(t+1))$ is included in the replay memory $\mathcal{M}$.

iii. Resource block Allocation

The transmission duration is segmented in N time slots $\mathrm{T} = \{\mathrm{t}_1, \mathrm{t}_2, \dots \mathrm{t}_\mathrm{N}\}$ and resource blocks are denoted as $\mathrm{R_b} = \{\mathrm{r}_1, \mathrm{r}_2, \dots \mathrm{r}_\mathrm{I}\}$ where total number of RBs are I. Vehicle platoons are denoted as $\mathrm{P(t)} = \{\mathrm{P}_1, \mathrm{P}_2, \dots \mathrm{P}_\mathrm{C}, \dots \ \mathrm{P}_{|\mathrm{P(t)}|}\}$ where C is the cluster index and $|\mathrm{P(t)}|$is the total number of clusters. Each platoon consists of platoon leaders and members. Vehicles that are not included by any platoon is denoted by$\mathrm{V}_\mathrm{I}^\mathrm{n}(\mathrm{t})$. Figure 7.3 describes the underlying flow diagram of resource block allocation. To enhance communication quality only leader vehicle constantly detects the sub-frames by evaluating the RSRP and the S-RSSI for all I sub-channels; and follow the sensing window value determined by the Q-learning outcome. $\mathrm{T_{sensing}}$ determines the last sub-frames vehicles need to be observed. Suppose sub-frame $\mathrm{sJ_n}$indicates the initial sub-frame after the sensing window selection. Then the sensing window at $\mathrm{sJ_n}$ can be represented by following setof single-sub-frame resources for the $\mathrm{i^{th}}$ sub-channel: $\{\mathrm{sJ}^\mathrm{i}_{\mathrm{n}-\mathrm{T_{sensing}}}, \dots, \mathrm{sJ}^\mathrm{i}_{\mathrm{n}-1}\}$. Then leader starts a selection window with a set of continuous sub-frames. The resource reselection interval (RRI) denotes the time gap between two back-to-back CAM transmissions. In between the sensing window vehicle detects and reserve the usable sub-frames within the section window. Platoon leader decides the RSRP threshold $\mathrm{P_{th}}$ to a minimum value $\mathrm{P_{min}}$ and launches all the sub-frames in the selection window; $\mathrm{SW} = \{\mathrm{sJ}^\mathrm{i}_{\mathrm{n}+\mathrm{T}_1}, \mathrm{sJ}^\mathrm{i}_{\mathrm{n}+\mathrm{T}_{1+1}} \dots, \mathrm{sJ}^\mathrm{i}_{\mathrm{n}+\mathrm{T}_2}\}$. Vehicle discards the contender sub-frames when the particular candidate is not detected at the time of sensing and the linear average RSRP for that particular contender is greater than $\mathrm{P_{th}}$. RSRP disbarring condition for the $\mathrm{k^{th}}$ sub-frame (the $\mathrm{i^{th}}$ sub-channel) in the selection window can be represented as $\frac{1}{\mathcal{H}}\sum_{\mathrm{h=0}}^{\mathcal{H}}$ RSRP $(\mathrm{sJ}^{\mathrm{i}}_{\mathrm{n+T_{1+k-T_{sensing}}+h.RRI}}) \geq \mathrm{P_{th}}$.Here, $\mathcal{H} = \frac{\mathrm{T_{sensing}}}{\mathrm{RRI}}$. When RRI is equals to 100ms and $\mathrm{T_{sensing}} = 1000\mathrm{ms}$ and $\mathrm{k} = 5$ then we find RSRP value through following 10 sub-frames {5, 105, 205… 905} and divide it by $\mathcal{H} = \frac{1000}{100}$ to look the average RSRP (list 1). If rest of the sub-frames in SW is less than 20% of the whole obtainable sub-frames then $\mathrm{P_{th}}$ is improved by 3dB. When more than 20% of possible channel resources are detected then the vehicle generates selection window with the first 20% of contender sub-frames which has the minimum average S-RSSI in set $\mathrm{R_B}$ (list 2). The CHV then allocates sub-frame from selection set to vehicles.

$$RSSI \sum_{h=0}^{\mathcal{H}}(sJ^{i}_{n+T_{1+k-T_{sensing}}+h.RRI}) \tag{7.8}$$

Vehicles can retain the same sub-frame for the subsequent resource counter (RC) and perform further transmission in the interval. When RC becomes zero, vehicle uses previously selected resources with the probability of p_b or reselect fresh resources for CAM transmission with a probability of (1-p_b). Each vehicle uses $T_{sensing}$ for detecting the possible sub-frames and further selecting the minimum RRI to make sure that there should be enough resources for each platoon vehicle [253].

iv. Priority-based Resource Dissemination

Different latency and reliability demand in this proposed methodology categorize vehicles. f is the fitness function which is the aggregative minimizing function with normalized QoS indexes. ω_1 and ω_2 are weighting factors. The fitness function is designed to prioritize the most reliable and low-latency vehicles for resource allocation. Q_i and L_i denotes the reliability and latency requirements respectively.

$$\min f = \omega_1 \times (-Q_i) + \omega_2 \times L_i \tag{7.9}$$

$$\text{Subject to: } \sum_{i=1}^{n} \omega_i = 1 \ldots \omega_i \in (0,1) \tag{7.10}$$

$$L_i \leq L_{max} \tag{7.11}$$

The platoon leader distinguishes the QoS requirements of member vehicles by this priority-setting methodology. The priority of each vehicle is populated depending on the latency and reliability requirement of vehicles.

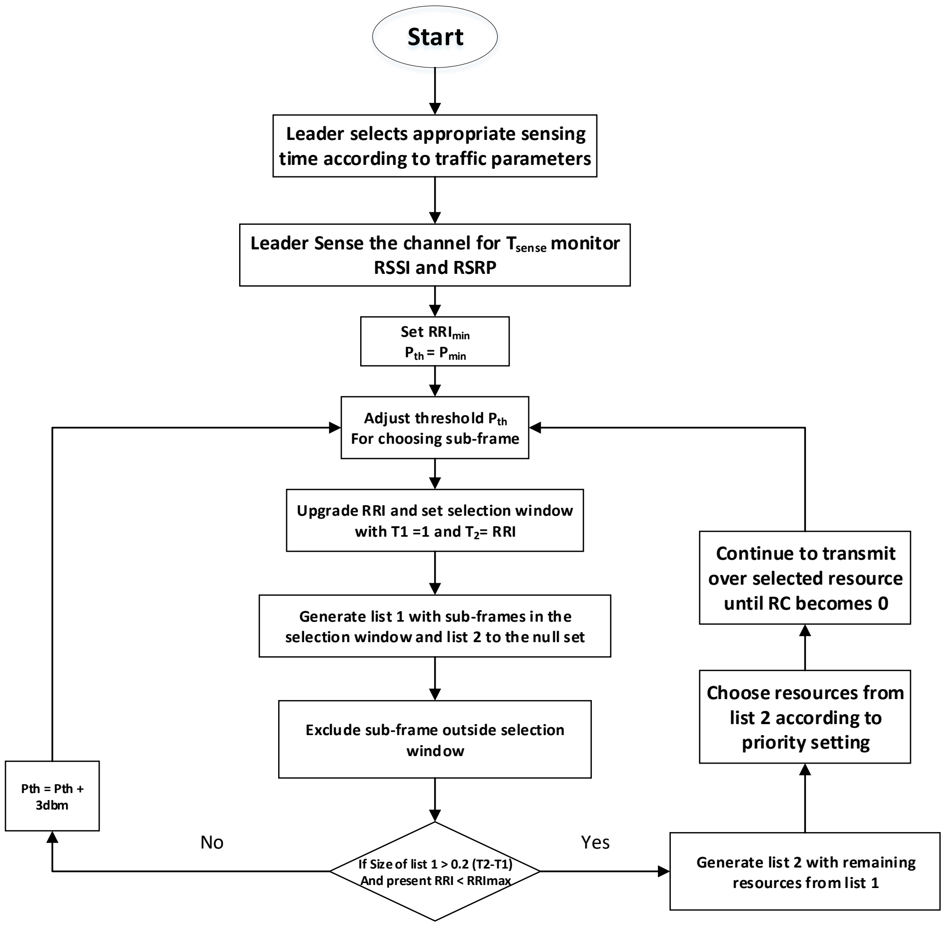


Figure 7.3 Flow diagram

7.2 Results and Discussion

In this section, the performance evaluation of CHQ-RA is compared with conventional SB-SPS and two existing works under different parameter settings.

Simulation Environment

Simulation is performed for V2X Mode4 type communication according to 3GPP recommendations. Vehicle traces are generated using the traffic simulator SUMO for a 10 × 10 grid network. Matlab-based LTEV2VSim [254] is used for three-lane two-way-based congested road ways. We have performed the simulations using a system consisting of a 16-core CPU, 32 GB RAM, and an Ubuntu18.04 operating system. The free flow speed of the vehicles is set to 45 km/h with an inter-vehicular gap of 2m. Vehicles generate CAMs at the rate of [10, 20, 30, 40, 50] packets per second (pps) with variable sizes of 190, 300 and 400 bytes. Table 7.2 shows the simulation parameters. Each CHV acts as an agent for the proposed work and sets the sensing time. Q-learning algorithm has one input layer, two hidden layers followed by one output layer. Adam optimizer is used to update network parameters. The model is trained for 10000 episodes where mini-batch size is 256 with the learning rate of 0.001 and discount factor of 0.99. In every training episode, ε-greedy policy is used where random action is chosen at probability ε and $arg\max_{a \in A} Q(s_t, a)$ is selected with the probability of $1 - \varepsilon$. At every time step CHV estimates the traffic status and accordingly it selects an action that has maximum Q value.

Simulation Parameters

Three pivotal performance evaluation parameters are considered for here to analyze efficacy of the proposed approach with the conventional one. It is obvious that vehicles frequently change lanes, accelerate decelerate and overtake that makes the environment vulnerable and unstable. To make the evaluation more impactful, simulation parameters need to be analyzed in terms of varying traffic, source to destination distance and transmission packet size.

Packet Reception Ratio: PRR is the ratio of number of successfully received CAMs to total number of CAMs are generated. Due to the packet collision induced by insufficient SINR, PRR ratio is decreased.

$$\frac{CAM_{Success}}{CAM_{Total}}$$

Collision Ratio: CR is the ratio of number of collision packets due to poor resource allocation to total number of transferred CAMs.

$$\frac{CAM_{collided}}{CAM_{Total}}$$

Table 7.1. Simulation Settings

Parameters	Settings
Carrier Frequency	5.9 GHz
Channel Bandwidth	10MHz
Number of Sub-channels	10
RB/sub-channel	10
Transmission power	23 dBm
Resource reservation period	50ms
Average speed of vehicles	45 Km/h
Modulation and coding scheme	QPSK
CAM size	190, 300,400 Bytes
Average length of selection window	20 ms
Threshold RSRP	-110 dBm

Update Delay: UD is the difference between two consecutive successfully received CAMs which will plays a significant contribution in network latency whereas T_j is the present timestamp of successfully delivered packet i.

$$\frac{1}{CAM_{Total}} \sum_{j=1}^{CAM_{Total}} T_j - T_{j-1}$$

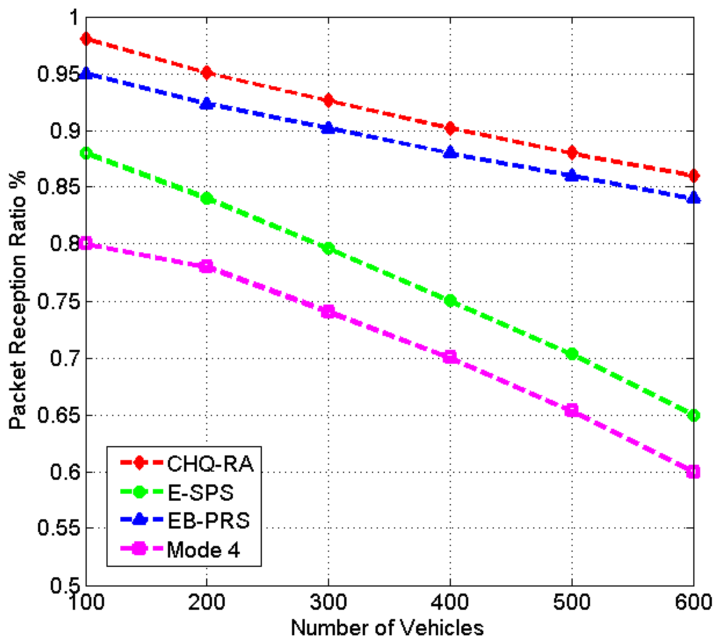
Analysis of PRR based on variable traffic density, CAM size and Tx-Rx distance

Figure 7.4 exhibits PRR results for the considered schemes and the proposed CHQ-RA when packets are transmitted at 10 pps for varying traffic densities (7.4. a), varying CAM size (7.4. b), and varying transmitter-receiver (Tx-Rx) distance (7.4. c). In Figure 7.4.a PRR decreases with the increase in traffic because of the scarcity of limited resources. PRR performance for the conventional mode 4 scheme is poor for varying traffic density compared with the EB-PRS [103], E-SPS [104], and proposed CHQ-RA. In the case of mode 4, when the vehicle number increases CAM generation also increases which induces resource conflicts. It is difficult to evaluate which resource is idle and which is occupied other nodes because of random resource allocation currently use. The improved scheme E-SPS performs better than mode 4 due to its better identification of available resources. The next improved scheme EB-PRS shows marginal improvement with E-SPS when traffic density is low and gives better results when traffic density is high. EB-PRS outperforms the prior compared schemes due to its resource-updating mechanism based on collision detection, which enhances its PRR in dense traffic environments. CHQ-RA outperforms the compared schemes, especially in dense traffic scenarios due to its efficient handling of resources with the guidance of cluster heads that generates cooperative awareness about neighboring nodes and less amount of recurrent resource reselection. Urban traffic follows a repetitive manner that can be easily represented as platoons. The most stable vehicle performs the resource allocation task and distributes them according to the platoon vehicles' priority requirements with the sensing time estimation. CHQ-RA provides higher PRR with enhancement of 27.9%, 18.58% and 2.6% in comparison with conventional mode 4, E-SPS and EB-PRS respectively for pps = 10.

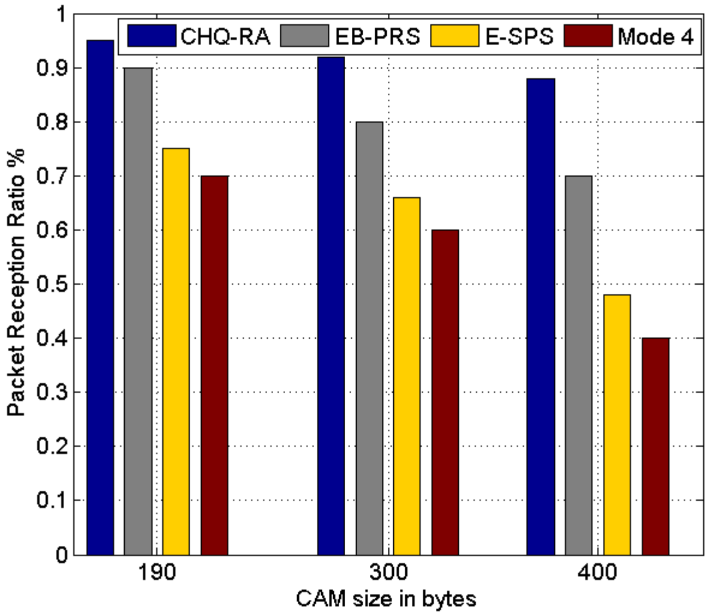
Figure 7.4. b depicts the analysis of average PRR performance when CAM size is upgraded from 190 to 400 bytes. It is evident from the results that when packet size increases from the standard size of 190 bytes overall PRR performance degrades. To transmit larger size packets more radio resources are required otherwise the transmission time to the destination vehicle will be longer. However, as there is always a maximum limit of delay, only way out to

handle larger packet sizes is to assign more resources to transmit the packets. Thus, the successful packet transmission rate is reduced due to the unavailability of resources for more vehicles. When CAM size is increased from the default size of 190 bytes to 400 bytes PRR of the proposed scheme CHQ-RA is reduced by 7.36%. When CHQ-RA scheme is compared with mode 4, E-SPS and EB-PRS, overall PRR improvement for CAM size 190 bytes are 35.7%, 26.6%, and 5.5% respectively. Meanwhile, for higher CAM size of 400 bytes PRR improvement is 25.7% for CHQ-RA compared to EB-PRS, which establishes the superiority of proposed framework.

In Figure 7.4. c, it can be observed that PRR performance degrades with the increased transmission radius. When the distance between the transmitter and receiver is increased packet drop happens because of the channel interference and collision, which is the result of poor SINR. As the available resource is fixed and the number of successful CAM transmissions is decreasing PRR performance degrades. Mode 4 underperforms in comparison with the E-SPS, EB-PRS, and CHQ-RA because of the poor resource re-selection for collision avoidance. EB-PRS performs better due to its collision detection-based resource detection strategy. In the case of the proposed scheme, each vehicle's link stability and delay requirement are considered for resource allocation, which aborts transmission failure possibilities that provide improved performance.



(a)



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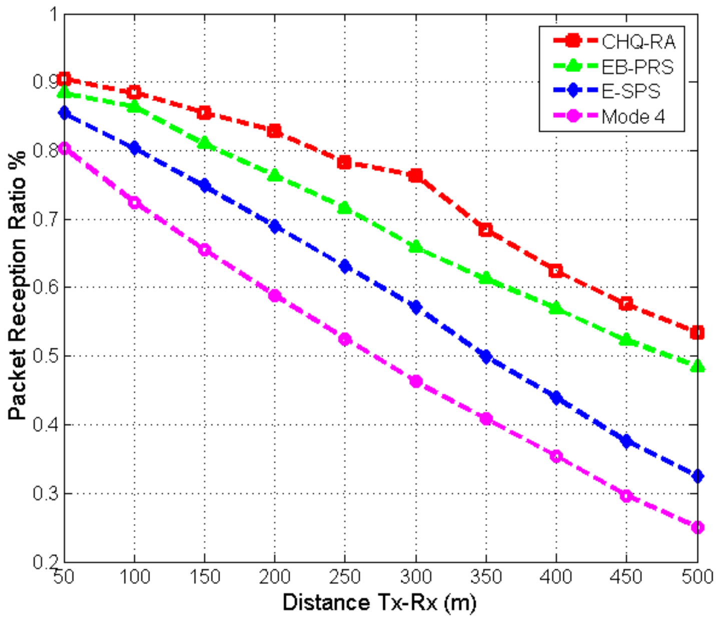
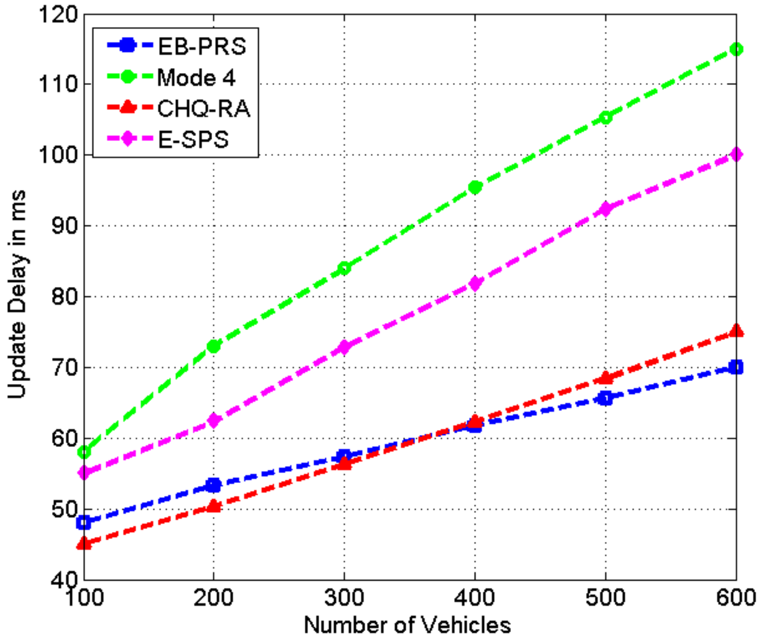


(c)

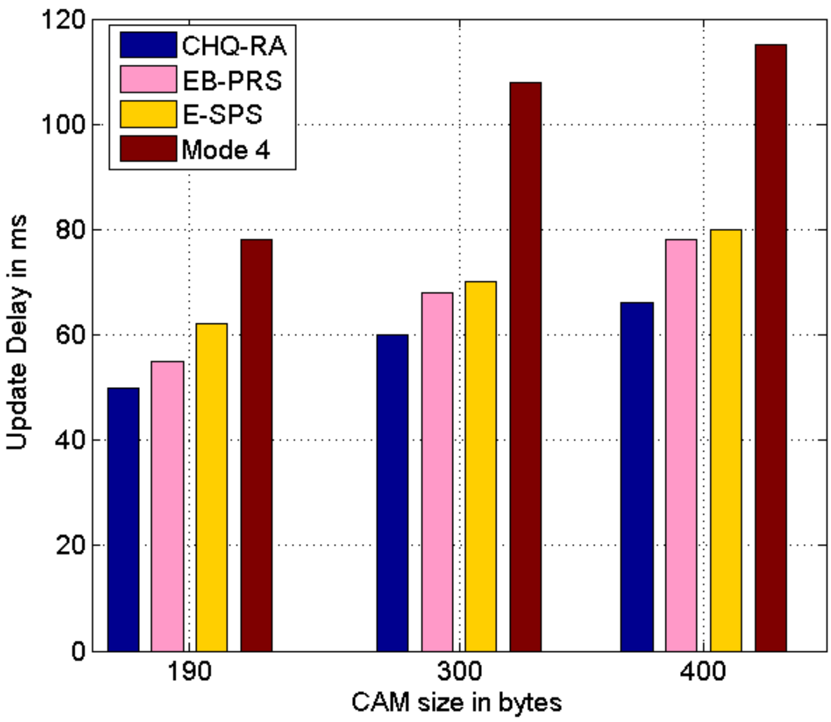
Figure 7.4. PRR vs. a. varying number of vehicles b. varying CAM size c. varying Transmitter-receiver distance with transmission rate 10 pps

Analysis of UD based on variable traffic density, CAM size, and Tx-Rx distance

Figure 7.5 depicts UD results for the considered schemes and the proposed CHQ-RA when packets are transmitted at 10 pps for varying traffic densities (7.5.a), varying CAM size (7.5.b), and varying transmitter-receiver (Tx-Rx) distance (7.5.c). Delays for the scenarios are directly dependent upon the successful reception of CAM. Therefore, PRR and CR performance are the deciding factors for UD evaluation. UD is inversely proportional to PRR and directly proportional to CR.



(a)



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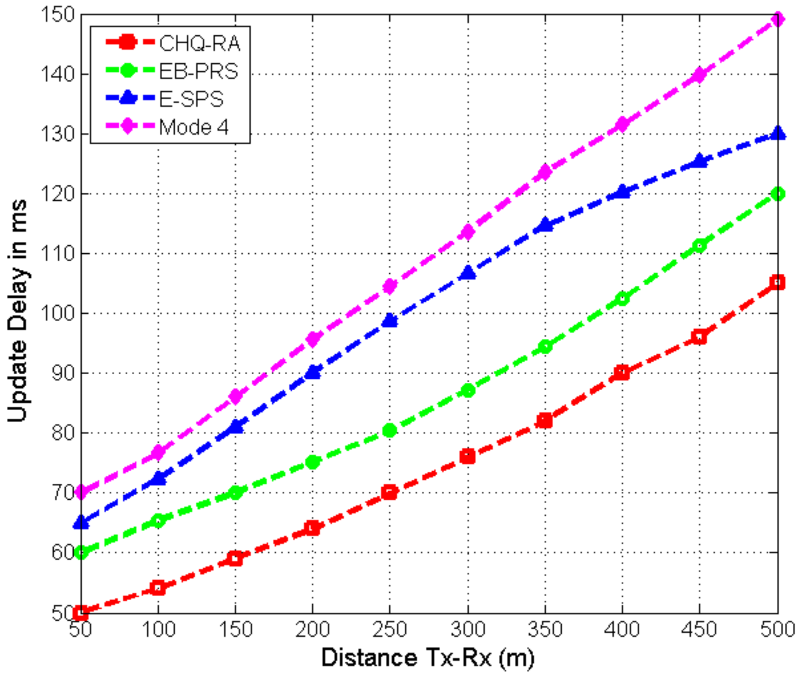


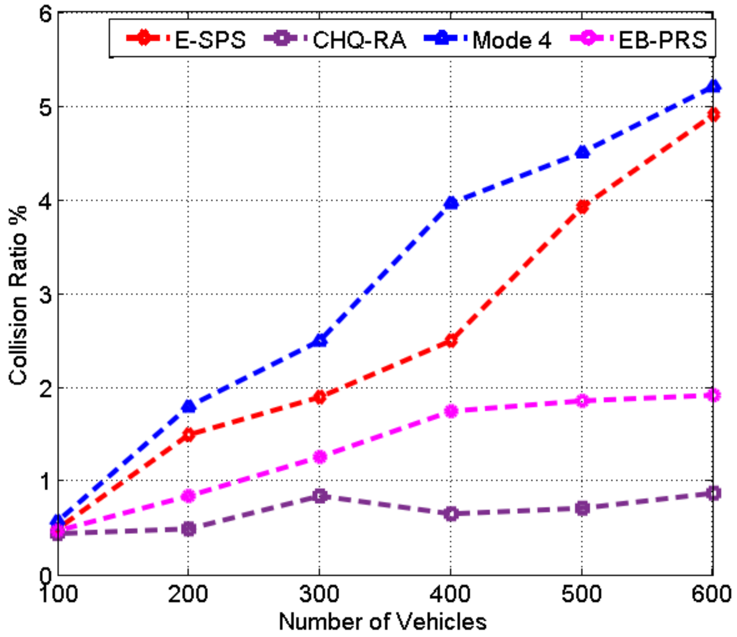
c.

Figure 7.5. UD vs. a. varying number of vehicles b. varying CAM size c. varying Transmitter-receiver distance with transmission rate 10 pps

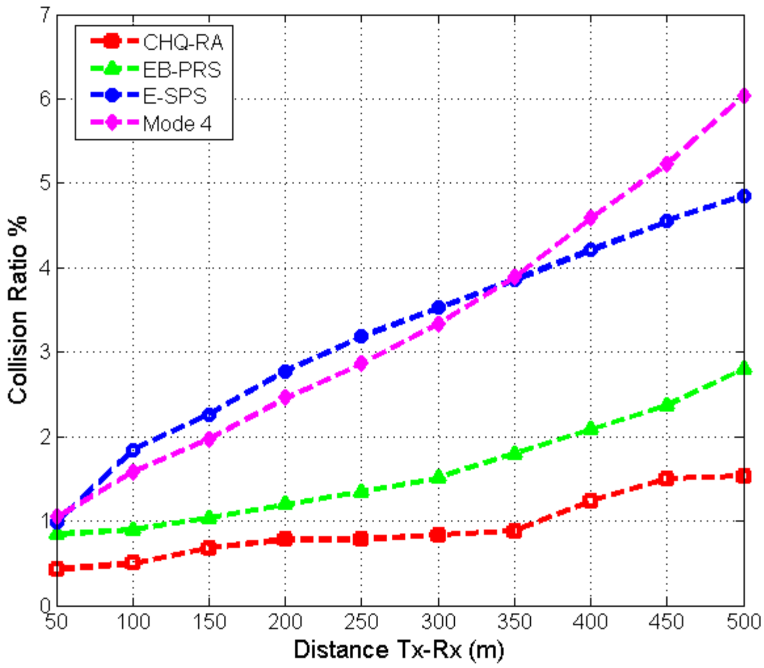
In figure 7.5.a, when the number of users is increasing mode 4 is unable to handle the resource allocation as most of the transmitted packets are wasted due to collision. CHQ-RA shows negligible decrement of UD compared with EB-PRS which is <1.5% whereas it generates better results when CAM size is increasing in Figure 7.5. b. EB-PRS performance deteriorates for larger CAM sizes due to the extra expenditure for blooms filter-based feedback generation, which is approximately 30 bytes. Compared with the EB-PRS the UD performance of CHQ-RA is reduced by 12.4% without hampering the PRR for a fixed pps rate.

Analysis of CR based on variable traffic density, CAM size, and Tx-Rx distance

Figure 7.6 plots CR results for the considered schemes and the proposed CHQ-RA when packets are transmitted at 10 pps for varying traffic densities (7.6. a), varying CAM size (7.6.b), and varying transmitter-receiver (Tx-Rx) distance (7.6. c). In Fig. 7.6 a, CR increases with the increasing number of users for all the compared schemes. As resources are selected from the list based on sensing, the collision probability will enhance when the number of vehicles increases due to the overlapping resource selection by vehicles. In mode 4, resources are allocated randomly which results in growing CR value due to collision of CAM. As per the expectation, CR in case of mode 4 is much greater that E-SPS, EB-PRS and proposed scheme CHQ-RA for the fixed pps based CAM transmission due to the unplanned distribution of resources by vehicles.



(a)



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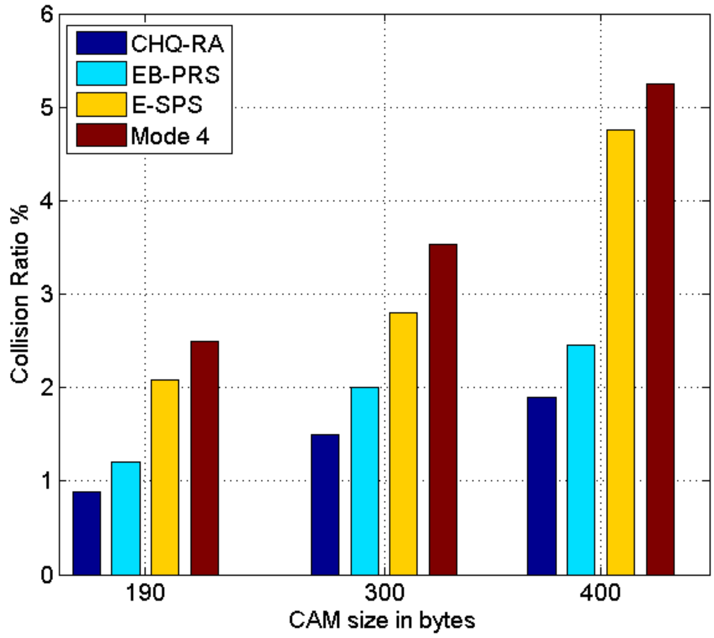


(c)

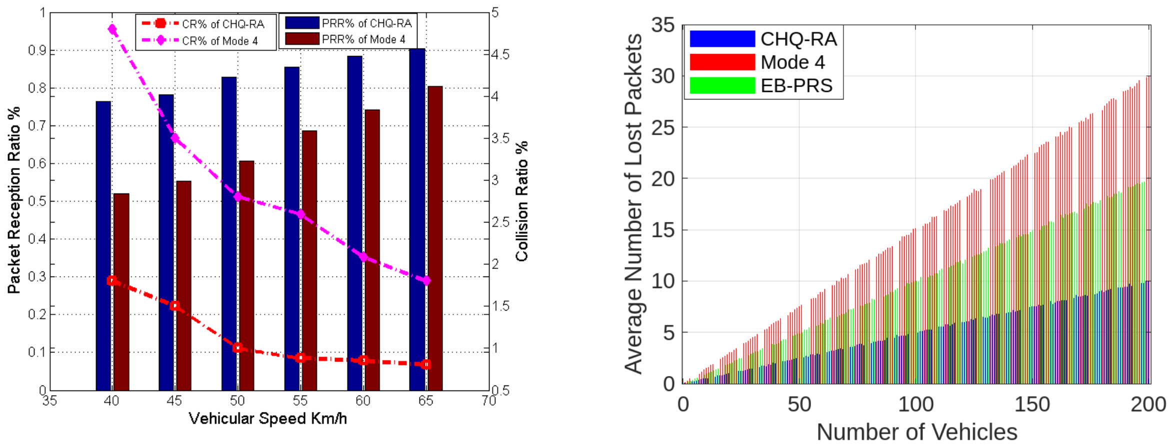
Figure 7.6. CR vs. a. varying number of vehicles b. varying CAM size c. varying Transmitter-receiver distance with transmission rate 10 pps.

When traffic density enhances CR also increases because of the choices made by the vehicles irrespective of the knowledge about the surroundings. EB-PRS shows reduced CR than E-SPS because it considers delivery estimation of the users that encounters CAM transmission failure. Both EB-PRS and CHQ-RA considers sensing time estimation that depends upon traffic density but still CHQ-RA provides lower CR in comparison with the former one due to the consideration of the fitness status of the adjacent vehicles, which is determined based on their reliability and latency performance. The continuous selection of resources by all the users' increases the network overhead which degrades network throughput where cluster head supervised mechanism enhances successful transmission and reduces co-channel interference that reflects in CR performance. With 10 pps CHQ-RA achieves performance improvement of -70%, -66%, and -40% in comparison with mode 4, E-SPS and EB-PRS respectively.

Analysis of PRR and CR based on vehicular speed

Figure 7.7.a illustrates that CHQ-RA significantly outperforms conventional mode 4 in terms of both Packet Reception Ratio (PRR) and Collision Ratio (CR) as vehicular speed increases. As speed rises, vehicular density decreases, resulting to a corresponding increase in PRR. When

vehicular speed is less which implies traffic is congested, CHQ-RA delivers much stable performance in comparison with mode 4 in such scenarios. Conversely, at lower speeds, more vehicles are present for CAM transmission, resulting in a higher likelihood of packet collisions. Our findings establish that CHQ-RA experiences a lower collision ratio compared to mode 4, particularly at varying vehicular speeds. To achieve more insights regarding the performance in Figure 7.7.b, we analyzed the average number of lost packets with respect to number of vehicles for mode 4, EB-PRS and proposed CHQ-RA. This shows the supremacy of proposed scheme as less number of packets are lost compared to existing schemes when number of vehicles are increasing. Due to the high PRR percentage and low CR percentage of CHQ-RA, most of the packets are successfully delivered which directly reduces the number of lost packets.



(a) (b)

Figure 7.7.a. PRR and CR vs. vehicular speed b. Average number of lost packets vs. number of vehicles

Analysis of PRR and UD vs. Transmission rate

Figure 7.8 exhibits the PRR and CR comparison for varying transmission rate, which is varied from 10 to 50 pps with traffic density of 200 veh/km. It can be observed that when the transmission rate increases, PRR performance degrades and CR values increases for mode 4 as well as other schemes. Mode 4 and EB-PRS provides almost similar performance at high transmission rate 40 pps whereas CHQ-RA shows small performance enhancement for PRR. Table 7.2 exhibits the performance comparison of PRR and UD under varying traffic densities for default pps 10 and higher pps 50. Low, medium and high traffic densities are implemented as 100, 400 and 800 vehicles respectively over a one km roadway in the simulation. For low traffic density, mean PRRs are 0.97, 0.90, 0.81 for CHQ-RA, EB-PRS, conventional mode 4 respectively when transmission rate is in default value fixed as 10 pps. For the same scenario, higher pps 50 will affect mean PRR values and it reduces into 0.92, 0.80, and 0.71 for CHQ-RA, EB-PRS, and conventional mode 4 respectively.

Table 7.2: Comparison of PRR and UD performances for different pps under varying traffic scenarios

Traffic Density	Evaluation Parameters	pps=10			pps=50		
		CHQ-RA	EB-PRS	Mode 4	CHQ-RA	EB-PRS	Mode 4
Low Traffic Density	PRR	0.97	0.90	0.81	0.92	0.80	0.71
	UD (ms)	40	47	60	46	55	62
Medium Traffic Density	PRR	0.90	0.82	0.68	0.81	0.75	0.68
	UD (ms)	55	60	110	57	64	110
High Traffic Density	PRR	0.86	0.70	0.52	0.70	0.65	0.61
	UD (ms)	72	88	125	88	110	128

From the extensive performance evaluation, it is evident that CHQ-RA generates more stable and enhanced output in diverse scenarios, making it robust and more suitable for adapting dynamic vehicular networks.

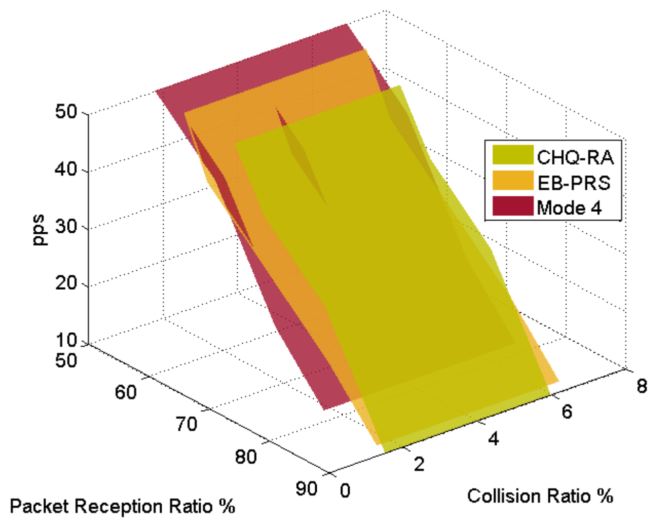


Figure 7.8 PRR and CR vs. pps with 200 veh/km

7.3 Chapter Summary

This paper introduces a novel resource allocation framework for C-V2X (Cellular Vehicle-to-Everything) communications, entitled as CHQ-RA, which leverages cluster head-aided resource management to enhance stability and reliability in connected vehicular environments. Existing resource allocation schemes in V2X often face difficulties with resource overlapping and packet loss due to high vehicle density, leading to degraded communication quality. CHQ-RA addresses these challenges by using an adaptive Q-learning-based mechanism for sensing time allocation and real-time idle resource detection, taking traffic density into account. The framework incorporates a fitness function that prioritizes vehicles based on their reliability and latency needs, customized for URLLC (Ultra-Reliable Low Latency Communication) scenarios to improve quality of service. Simulation results demonstrate CHQ-RA outperforms in comparison with conventional methods, showing improvements in packet reception ratio (PRR), collision rate (CR), and update delay (UD). The framework's robustness is evaluated according to various scenarios with varying vehicular densities, CAM sizes, and transmitter-receiver distances, validating that it sustains high performance under varying conditions. Significantly, when traffic density changes from low to high, CHQ-RA exhibits an 11% reduction in PRR, compared to a 35% drop in PRR for conventional mode 4 at a fixed rate of 10 packets per second (pps). This indicates that CHQ-RA is a potential solution to support more reliable and secure vehicular communication in future V2X networks, especially under diverse and dense traffic conditions.

- ❖ Publications from this chapter

1. Sreya Ghosh, Iti Saha Misra, Tamal Chakraborty, "Intelligent sensing based resource allocation using Q Learning with improved performance in 5G-V2X networks" Communicated to International Journal of Communications Systems Wiley.

8
Conclusion and Future Scope

8. Conclusion and Future Scope

8.1 Introduction

"There is no real ending. It's just the place where you stop the story."

Frank Herbert, American author

We have been witnessing outstanding improvements on designing, developing and implementing intelligent transportation systems intend to enhance road safety, smooth traffic and cleaner environment. Moreover, allowing vehicles to interact with service providers whenever necessary. This is contemplated as an effective solution towards delivering an affordable and smart transportation system. In 2011, IEEE brings the IEEE 802.11p standard for the wireless access in ITS entitled as DSRC (dedicated short-range communication) for the successful implementation of vehicular communication addressing its rapid mobile environment. Further, due to the notable advancement in information and communication technologies (ICT), ITS can be collaborated with internet by transferring data using long distance cellular technologies like 4G/LTE, 5G. However, the prior mentioned benefits of ITS do not come without its own challenges from the perception layer, network layer to application layer. At the perception layer or more precisely physical layer, the main challenges include gathering information from traffic sensors about the transportation environment preserving the QoS needs *under* rapid mobile environment. At the same time, at the network layer, the primary challenges are i) transferring and processing of data with efficiently handing them ii) reducing of the cost of data transmission over the backhaul iii) connecting to the servers, infrastructures, traffic lights for traffic monitoring and management. While, at the application layer is responsible for generating application specific services for the commuters. In this thesis, we address the aforementioned challenges by building an ITS through the applications of vehicular ad-hoc networking (VANET) technologies. For the vehicular nodes, we employ delay sensitive and QoS enabled routing protocols to maximize their performance under all conditions. Whereas at the infrastructure, we exploit transportation network as connected graphs and use them to distinguish crucial intersections for infrastructure placement to minimize deployment cost, utilize the bandwidth at the maximum, and provide coverage for traffic monitoring and controlling. In the application phase, we explore the aspects of congestion control, efficient path planning, and reduction of pollution generation.

This chapter delivers a concise summary of the research fulfilments executed in this thesis, as specified by the overall objectives of the research (stated in Chapter 1), and also points out the future possibilities of system and application development that can be proceeded based on the derived outcome in the thesis.

8.1.1 Summary of Research Accomplishments and Conclusions

Sustaining network transmission coverage is one of the most essential requirements of VANET. However, the vehicular nodes' high mobility and the availability of numerous paths establish the dynamic topology of VANETs. RSUs deployment is one of the key solutions to handle the coverage issue, which authorizes the VANET to confirm stable connectivity. This thesis concentrates on techniques that enhance the transmission coverage and the connectivity of VANETs with the assistance of Roadside Units. By observing the relevant proposed frameworks in the context of RSU deployment as per our objective, we explored the attained results and their analysis. Several features, such as vehicular speed, traffic density, vehicle location, complex road architectures, routing protocols, QoS requirements, etc., generally influence the RSUs deployment. We have surveyed the existing works for optimal deployment of RSUs and analyzed them according to their objectives, placement, and applications. Additionally, we manifested that optimal and reduced deployment of RSUs are more practical and impactful when the huge deployment cost is taken into consideration. To encounter with the limitations of the reviewed studies stated in the literature, a significant research contribution been made in this thesis regarding infrastructure placement.

IIA-ORD, an intersection Influence analysis system for optimal RSU deployment, can ***handle larger areas with a reduced number of RSUs.*** We validated IIA-ORD with extensive results analysis using two road topologies imported from real-world maps. Compared to the three existing approaches: CDA DC/CC, random, and IHDA the obtained results illustrated the effectiveness of the proposed formulation in terms of number of RSUs placed, the average coverage ratio, coverage time ratio, and contacts per trip. To establish the application perspective, we built a traffic prediction framework with the proposed RSU deployment system and compared it with placing the RSUs throughout all the intersections.

Further, we triggered by the requirement to build agile routing protocols for VANET scenarios that can accommodate the exchange of data packets with stringent QoS constraints, such as high data rate and low network latency within rapid mobile environment. While fundamental MANET algorithms have been preliminarily applied to serve vehicular applications information propagation in their infancy, researchers identified the requisite for more sophisticated solutions to fulfil the strict QoS demand of the vehicular network. Metaheuristics paradigms have enormous applicability in solving complex optimization problems. Two significant research contributions have been made to address the problem of network overhead and the need for reliable and fast message delivery through designs and implementations of novel VANET routing algorithms that exploit bio-inspired technologies.

Reduced route overhead by ant colony optimization (RRO_ACO) an ACO-based routing protocol that reduces excess packet forwarding by incorporation of acknowledgment packet broadcasting while ACO ensures identification of the most stable route for information transmission through the utilization of pheromones. To verify this, RRO_ACO is compared with RDACO and RAGR for throughput, PDR, and network latency. Furthermore, the ***Canine olfactory route-finding algorithm*** utilizes RSUs caching capability to remember the already traversed routes used for packet transmission up to a certain time limit so that route discovery can be avoided which saves channel usage and reduces E2E delay. While vehicles discover routes through control packets it broadcasts link and time attributes that help to identify stable routes and stop control packet transmission from each node of a hop, which alleviates the occurrence of broadcast storm situation. Through extensive result analysis based on an imported real-world map, we observed that the developed algorithm outperformed the state-of-the-art geographical and topological routing protocols in terms of PDR, throughput, delay, and overhead while considering varying data packet size, vehicular density, vehicular speed, and source to destination distance. The above research findings gave us a meticulous understanding of how routing protocols for traffic data dissemination function and how they can be enhanced. After suitably designing the infrastructure placement system and packet forwarding algorithms for ITS, the focus shifts to the application-specific areas considering adverse traffic conditions, followed by smart functionalities of ITS to achieve smoother and cleaner transportation. ***To this end, a controlled speed limiting system for congestion mitigation in smart cities*** is developed which is a variable speed limiting system where RSUs are used to assist vehicles with speed limits so that traffic jams at intersections due to accumulation of vehicles can be avoided. This framework induces smooth traffic with reduced travel time and increased speed.

Thereafter, an application for ITS for emergency health care is developed that not only suggests appropriate healthcare destinations according to users' preferences but also provides convenient route guidance to reach there. Multi-criteria decision-making algorithm TOPSIS is used to analyze available hospital resources and based on that it suggests the healthcare destination and path planning is done by incorporating a bio-inspired firefly algorithm. ***In the next phase of research enhanced A* Algorithm is proposed to reduce CO_2 emission and fuel consumption in ITS.*** This algorithm not only observes the shortest distance to re-route vehicles but also considers the frequency of usage of the road and present road conditions. Only private vehicles are considered for re-routing as public transport follows the fixed route, which cannot be altered. Traffic congestion and frequent acceleration/deceleration of vehicles are minimized as a result, travel time and fuel consumption are also reduced. This proposed algorithm performs better than the Dijkstra and A^* algorithms for the performance evaluation metrics. ***Further, intelligent traffic management for smart cities using federated learning-based congestion predictions is designed to enhance transportation efficiency in terms of reduced travel time, pollution, and increased vehicular speed.*** As RSUs are placed optimally in crucial intersections, they cannot manage the traffic of the overall area. Central cloud server is used to handle the overall distributed RSU network and the RSUs do not cover the areas. Federated learning is an emerging technology, which is a distributive machine learning methodology is incorporated here for traffic predictions. RSUs predict local traffic within its coverage area based on a bidirectional LSTM module. Each connecting roadway traffic is estimated by the decisive weight. Weight is determined based on the traffic parameters like vehicular speed, density, acceleration, and travel time of the connecting edge. A large-scale simulation area is taken from Kolkata's open street map which is considered for extensive simulation study where the proposed approach is outperformed in comparison with the existing schemes. Prediction model performance is evaluated based on accuracy and loss whereas delay analysis is also included to establish the importance of federated learning. ***Lastly, this thesis has significantly enhanced resource allocation for C-V2X Mode 4 communication through the CHQ-RA framework.*** The growth of connected and autonomous vehicles (CAVs) has underlined the critical importance of efficient vehicular communication technologies in ensuring safer and more efficient transportation systems. Cellular Vehicular-to-Everything (C-V2X) communication, particularly in Mode 4, follows a decentralized mechanism for vehicles to communicate directly without infrastructure support. It faces several challenges such as packet collisions, overlapped resource allocation, and inefficient handling of dynamic traffic conditions, which degrade QoS requirements. To overcome these challenges, this thesis proposed a novel resource-allocation framework named **Cluster Head Vehicle-assisted Q-learning-based Resource Allocation (CHQ-RA)**.

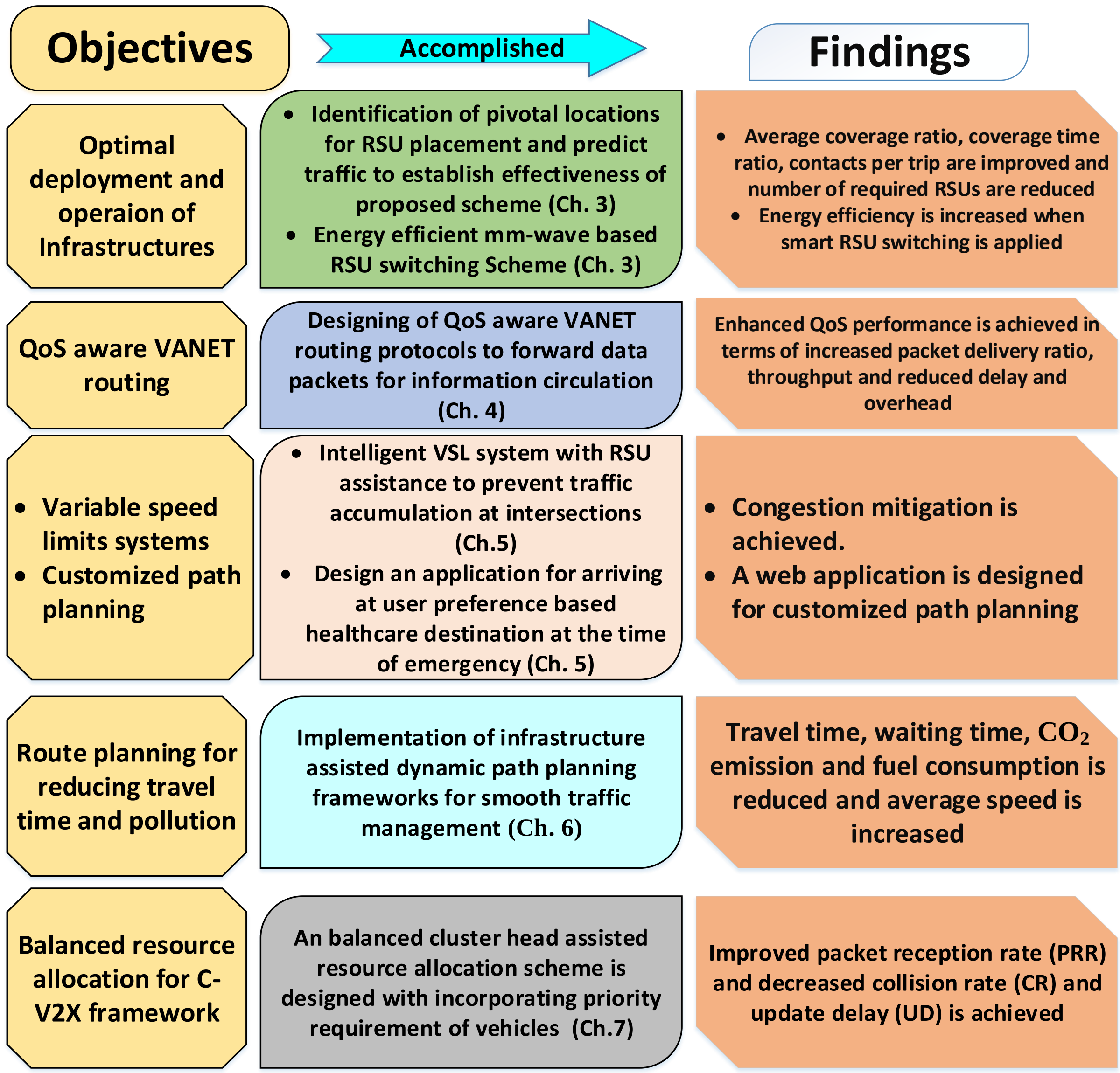


Figure. 8.1 Accomplishment of the research objectives in the thesis

In this approach Cluster Head Vehicles (CHVs), selected based on their stability indices, supervise resource allocation within clusters. By integrating a Q-learning-based paradigm, CHQ-RA dynamically adjusts sensing windows and optimizes resource dissemination among cluster members based on link stability, and latency requirements.

In brief, the research in this thesis suitably carries out overall objectives through contemporary research domains: i) *facilitating cost-efficient RSU deployment through detailed analysis of complex network analysis*, ii) *enabling QoS-efficient data packet transmission with VANET routing protocols*, iii) *designing ITS applications for congestion management and pollution minimization*, and *iv. Balanced resource allocation for transmitting Cooperative Awareness Messages (CAMs) in C-V2X networks.* Figure 8.1 expresses this suitably.

8.2 Future Scope

This thesis presents a rigorous background study and fruitful contributions to implementing successful and impactful ITS that assure social, economic, and environmental enhancements. The quest for improvement has no end, which drives us to distinguish some future directions of this research.

1. The convergence of 5G and 6G technologies carries transformative potential for Intelligent Transport Systems (ITS) and the Internet of Vehicles (IoV). Incorporation of these paradigms offer ultra-high-speed data transfer, near-zero latency, and massive connectivity. These advancements aid seamless V2X communication, supporting real-time applications such as autonomous driving, adaptive traffic management, predictive maintenance, and energy-efficient transportation. The foundation of these capabilities lies in efficient data collection and processing at the device or sensor level, coupled with decision-making at the edge, where vehicular sensors facilitate load balancing and task scheduling. With 5G as a crucial factor and 6G pushing the boundaries further, integrating edge computing into IoV can optimize system performance while enabling energy harvesting within VANETs. Incorporating terahertz communication and AI, 6G will increase sensing capabilities for meticulous environmental awareness, advanced object detection, and real-time decision-making. At the same time, IoV with edge analysis will address resource allocation and task optimization that helps to create a sustainable and intelligent framework for future transportation systems. Future research should focus on overcoming challenges like signal propagation at high frequencies, energy optimization, robust security measures, and effective integration of 5G and 6G technologies with edge computing. This unified approach will accelerate the way for hyper-connected, intelligent, and environmentally sustainable transportation ecosystems.
2. Security perceptions should be taken into consideration. Vehicular networks require the exchange of accurate and current traffic information for properly functioning; they are vulnerable to various attacks that are made by misbehaving nodes, which may transfer false data that leads to potentially alarming situations. Specifically, these internal attacks have a huge impact on collision avoidance approaches, which require effective exchange of information so that road accidents can be eliminated. Hence, we aspire to

incorporate misbehaviour detection aspects in routing algorithms that looks over information accuracy before executing ITS applications.

3. The VSL system proposed in this thesis in Chapter 5 does not consider the three-way or four-way intersections. Hence, it may be included in the system model in the future. Moreover, throughout the research work the vehicle length and the in-between safety gaps between them is same which is not the ideal case. The diversity among vehicle classes with dissimilar attributes or mixed traffic influences congestion patterns, traffic parameters, and road resource management. This needs to be considered in the traffic prediction model hereafter.
4. Further work can focus on integrating Integrated Sensing and Communication (ISAC) technologies into Intelligent Transport Systems (ITS) and Vehicular Ad-hoc Networks (VANETs). ISAC combines communication and sensing, enabling real-time data sharing for advanced applications like object detection, collision avoidance, and adaptive traffic control. Research could develop ISAC-enabled protocols for efficient spectrum sharing, delay-sensitive communication, and energy optimization. Machine learning can enhance ISAC operations through adaptive beamforming and real-time decision-making. ISAC can also support cooperative automated driving by improving vehicle positioning, obstacle detection, and infrastructure monitoring for safer and more efficient transport. Challenges include managing interference, securing data, and testing in real-world conditions. Standardization efforts will ensure compatibility and scalability. By adopting ISAC, ITS can achieve smarter, safer, and more efficient mobility systems.

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