UNIVERSITI TEKNOLOGI MARA

# AN OPTIMIZED INTERNET OF VEHICLES NETWORK FOR SAFETY-BASED MESSAGES TRANSMISSION USING PARTICLE SWARM OPTIMIZATION

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PhD

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**SHAHIRAH BINTI MOHAMED HATIM**

Thesis submitted in fulfilment
of the requirements for the degree of
**Doctor of Philosophy**
**(Computer Science)**

**Faculty of Computer and Mathematical Sciences**

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## CONFIRMATION BY PANEL OF EXAMINERS

I certify that a Panel of Examiners has met on 26th January 2026 to conduct the final examination of Shahirah Binti Mohamed Hatim on her Doctors of Philosophy thesis entitled “An Optimized Internet of Vehicles Network for Safety-based Messages Transmission using Particle Swarm Optimization” in accordance with Universiti Teknologi MARA Act 1976 (Akta 173). The Panel of Examiners recommends that the student be awarded the relevant degree. The Panel of Examiners was as follows:

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ABSTRACT

This thesis addresses the problem of traffic congestion, which arises from increased vehicular queuing when the packet transmission load in the network exceeds the available buffer capacity. This condition leads to slower travel speed and also delays in travel time. Many urban cities worldwide have experienced severe congestion challenges. However, with the aid of the Internet of Things (IoT), the traffic congestion problem in the event can be managed effectively as vehicles are now equipped with sensors, actuators, data acquisition and communication systems that enable inter-vehicle communication. The Internet of Vehicles (IoV) has emerged as a key mechanism in in managing traffic congestion within modern Intelligent Transportation Systems (ITS), providing extensive opportunities for safety and mobility applications. This networking technology, provides vehicles with endless possibilities of applications including safety-related applications. Due to the high speed, dynamic mobility and unstable connectivity of vehicular nodes, maintaining stable IoV network performance remains a challenge. Previous research has explored various congestion control optimization techniques such Genetic Algorithm, Ant Colony and Ant Bee Colony for vehicular networks. While these methods improved performance to some extent, they often suffer from high computational complexity or slow convergence, limiting their suitability for real-time IoV environments. The recent proliferation of IoV network has emphasized the need for high Quality of Service (QoS) requirements in all networking scenarios. This study provides a comprehensive evaluation of the impact of vehicular mobility on IoV network performance. The analysis focuses on key QoS metrics, namely throughput, packet delivery ratio (PDR) and delay, while examining the relationship between mobility factors and medium access behaviour under varying network conditions. In achieving better performance in the QoS of the IoV network, a bio-inspired optimization approach based on the Particle Swarm Optimization (PSO) algorithm is proposed to mitigate network performance degradation caused by high node mobility. Vehicle mobility data is obtained from traffic flow simulation in SUMO and the network simulation phase is conducted in OMNeT++. Safety messages are disseminated among vehicles within the network. The experiment for the IoV network is concluded by optimizing the transmission rate to minimize the delay as the objective function in PSO algorithm. To ensure stable performance evaluation under dynamic vehicular conditions, simulations were conducted using varying simulation times and numbers of vehicles to capture both temporal network behaviour and traffic density variations. Under these settings, the throughput of the IoV network recorded average improvements of up to 23% and 14% after optimization. Packet delivery ratio (PDR) was also enhanced, with average gains of up to 37% and 15%, while network delay was reduced by up to 12% and 15% across different simulation times and vehicle densities. These results highlight the effectiveness of the optimization in improving IoV network performance under diverse conditions. The proposed PSO-based approach introduces a dynamic transmission rate control mechanism that adapts to vehicular density, effectively reducing congestion on the control channel. Overall, the findings highlight the potential for future research and practical applications in vehicular communication systems.

Keywords: Traffic congestion, safety-based messages, Internet of Vehicles (IoV), Particle Swarm Optimization (PSO)

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# LIST OF ABBREVIATIONS

**Abbreviations**

| | |
|---|---|
| AI | Artificial Intelligence |
| AR | Augmented Reality |
| ITS | Intelligent Transportation System |
| VANETs | Vehicular Adhoc Networks |
| VR | Virtual Reality |
| MANET | Mobile Adhoc Network |
| IoT | Internet of Things |
| IoV | Internet of Vehicles |
| RSU | Road Side Units |
| OBU | On-Board Units |
| OMNeT++ | Objective Modular Network Testbed in C++ |
| V2V | Vehicle-to-Vehicle |
| V2I | Vehicle-to-Infrastructure |
| V2X | Vehicle-to-Everything |
| V2C | Vehicle-to-Cloud |
| V2P | Vehicle-to-Pedestrian |
| V2S | Vehicle-to-Sensor |
| V2R | Vehicle-to-Roadside Unit |
| IR | Industrial Revolution |

| | |
|---|---|
| PSO | Particle Swarm Optimization |
| GA | Genetic Algorithm |
| ACO | Ant Colony Optimization |
| ABC | Ant Bee Colony |
| WSN | Wireless Sensor Network |
| CH | Cluster Head |
| CCH | Control Channel |
| SCH | Service Channel |
| SUMO | Simulation of Urban Mobility |
| PDR | Packet Delivery Ratio |
| QoS | Quality of Service |
| SDN | Software Defined Network |
| C4I | Command, Control, Communications, Computers and Intelligence |
| POI | Point of Interest |
| DoS | Denial of Service |
| GPS | Global Positioning System |
| BDS | BeiDou Navigation Satellite System |
| DSRC | Dedicated Short Range Communications |
| WAVE | Wireless Access in Vehicular Environments |
| RWP | Random Waypoint |
| RD | Random Direction |

| | |
|---|---|
| RW | Random Walk |
| GMM | Gauss-Markov |
| NHPP | Non-Homogeneous Poisson Process |
| FANET | Flying Adhoc Network |
| UDP | User Datagram Protocol |
| TCP | Transmission Control Protocol |
| GUI | Graphical User Interface |
| PSR | Packet Success Ratio |
| CBR | Channel Busy Ratio |
| GP | Genetic Programming |
| EP | Evolutionary Strategies |
| DE | Differential Evolution |
| FSA | Fish Swarm Algorithm |
| ML | Machine Learning |
| QPSO | Quantum Particle Swarm Optimization |
| ATC | Available Transmission Capacity |
| WSM | Weighted Sum Method |
| CM | Conic Method |
| TSP | Travelling Salesman Problem |
| EVRP | Electric Vehicle Routing Problems |
| HACO | Hybrid Ant Colony Optimization |
| HC | Hill Climbing |

| | |
|---|---|
| UTRP | Urban Transit Routing Problem |
| CAVDO | Metaheuristic Dragonfly-based Clustering Algorithm |
| VNR | Virtual Network Request |
| VNE | Virtual Network Embedding Algorithm |
| MAC | Medium Access Control |
| BDF | Broadcast Distance Factor |
| IVC | Inter-Vehicular Communication |
| TraCI | Traffic Control Interface |
| OSPF | Open Shortest Path First |
| RIP | Routing Information Protocol |
| GIS | Geographic Information System |

# CHAPTER 1
# INTRODUCTION

## 1.1 Introduction

The technological advancement of the automotive industry brings a significant impact on various domains including urban development and mobility, users' experience, cost and safety (Rahim et al., 2020). The number of vehicles on the road are increasing rapidly especially in urban areas day to day due to the needs of using transportation for travelling purposes. According to the statistics gained from Malaysia Automotive Association, the total of 799,731 new personal and commercial vehicles were registered in Malaysia by the end of December 2023, whereas 720,658 vehicles registration were recorded at the end of December 2022. Table 1.1 shows the registration of the new vehicles from the year 2010 to 2023.

Table 1.1
The Summary of the Registration of Passenger and Commercial Vehicles from 2010 to 2023

| Year | Passenger Vehicles | Commercial Vehicles | Total Vehicles |
|---|---|---|---|
| 2010 | 543,594 | 61,562 | 605,156 |
| 2011 | 535,113 | 65,010 | 600,123 |
| 2012 | 552,158 | 75,575 | 627,733 |
| 2013 | 576,640 | 79,104 | 655,744 |
| 2014 | 588,348 | 78,139 | 666,487 |
| 2015 | 591,275 | 75,402 | 666,677 |
| 2016 | 514,594 | 65,491 | 580,085 |
| 2017 | 514,675 | 61,950 | 576,625 |
| 2018 | 533,202 | 65,512 | 598,714 |
| 2019 | 550,179 | 54,108 | 604,287 |
| 2020 | 480,971 | 48,543 | 529,514 |
| 2021 | 452,663 | 56,248 | 508,911 |
| 2022 | 641,773 | 78,885 | 720,658 |
| 2023 | 719,160 | 80,571 | 799,731 |

Source: Malaysia Automotive Association, 2024

The observation from Table 1.1 shows that there is an increasing number of new vehicles produced every year. Recently, there is an increment of approximately 10.97% of the registration of vehicles in 2023 compared to the previous year. In addition, Malaysia is proven to be the third highest country in the South East Asia region to have more than one private ownership of cars (Suhaimi, 2023; Musa, Noor & Marjan, 2019; Ali et al., 2019). This situation strongly contributes to traffic congestion especially in the urban city such as Federal Territory of Kuala Lumpur since it recorded the highest number of vehicles registration, which is 80,900 vehicles in 2023 and 61,748 vehicles in 2022 respectively (Malaysia Automotive Association, 2024; Malaysian Transportation Statistics, 2023; Malaysian Transportation Statistics, 2022; Musa, et al., 2018). The traffic congestion of the urban city is seen to be seriously troublesome, complex, and expanding issue in both developed and developing countries (Suhaimi, 2024; Rasheed et al., 2020; Ali et al., 2019; Musa et al., 2018). It can be defined as the consequence of the imbalance traffic flow where the number of vehicles circulates on a specific zone increases to the peak level and exceeds the limit of possible capacity. The indicators of traffic congestion can be detected as the Quality of Services (QoS) are affected; extensive travel times, longer excursions and increased traffic flow (Tapas et al., 2023; Rahman & Hoque, 2018; Yang et al., 2014). Therefore, there is a growing demand for a real-time collision avoidance and warning technology to improve data transmission for safety messages and applications.

The Internet of Vehicles (IoV) network is a new cyber-physical system which consists of smart vehicles on the road, provide useful communication services intelligently among arbitrary-formed collections of vehicles that are geo-located and with other infrastructures (vehicle-to-everything (V2X)) via Internet connection. IoV network is evolved from Vehicular Adhoc Networks (VANETs) with the aid of Internet of Things (IoT). Vehicles in the network are known as individual mobile nodes (Zamrai et al., 2021; Akhtar & Moridpour, 2021). IoV network promotes high manageability, controllability, operationalization, and credibility involving multiple users, multiple vehicles, multiple things and multiple networks. In other words, the network owns the capabilities in obtaining, managing and computing large scale data of humans, vehicles, things and environments. These features are very important to improve the computability, extensibility and sustainability of complex network systems, thus reducing congestion (Raja & Bashir, 2020; Hahn, Munir & Behzadan, 2019).

There are two main categories of IoV applications which are safety and non-safety applications. The safety applications are essential and crucial in order to proactively alert drivers travelling in the IoV network to potential crashes and errors in advance. The objective is to prevent and minimize road accidents and reduce traffic congestion. Vehicles will be notified about traffic conditions depending on the destination and present location. If traffic is heavy on the route, drivers can save down on fuel and trip time by taking the alternative route. In addition, the traffic management can wirelessly communicate traffic information to vehicles at a specific place. The motorist will be able to make the right decisions and reach their destination more quickly and safely without delay (Zamrai et al., 2021; Fantian et al., 2017).

The implementation of safety message dissemination in IoV network with minimal delay is one of the main challenges to be solved. Despite the high scalability feature of IoV network as mentioned previously, unfortunately it still may lead to failures and network congestion since the success of the packet delivery rate for IoV network is reliable on it. This is due to the strong dependency on the number of mobile nodes and devices participated in the network which then causing network congestion (Zamrai, 2021; Chen et al., 2018). It is considered as a very important issue to be raised in the area. IoV network involving smart devices must be dynamic, where it should be able to handle dense network. Consequently, it would cause delays in message delivery due excessively loaded communication channel (Zamrai et al., 2021).

## 1.2 Research Background

Generally, a typical conventional method of city scale or road expansion to eliminate congestion are no longer effective; in terms of money, energy and environmental effects. Furthermore, it may cause a worsen traffic congestion (Jilani et al., 2023; Lu et al., 2021; Rahman & Hoque, 2018). Due to this condition, the architecture of traffic congestion control between the circulated vehicles in the cities under circumstances such as overcrowding during peak hour and natural disaster, is strongly needed to be imposed. The immediate effects that may occur in a very short time including disruption of road transport systems, traffic congestion, lengthy travel time, loss of productive hours, stress, exhaustion, as well as other stress-related issues (Tapas et al., 2023; Ismail, Ghani & Ghazaly, 2018).

Vehicular Adhoc Networks (VANETs) was introduced as a method to control and manage the congestion in urban cities. VANETs is an extended architecture of previous introduced Mobile Adhoc Networks (MANETs) that spreads information regarding the condition of the traffic acquired from one vehicle to another, as well as the road side units (RSUs) which are connected in the network. The information is transferred and gained via sensors and actuations. Furthermore, data acquisition and communication system on the traffic in VANETs is manipulated and can be shared in a wireless communication manner (Talib et al., 2017; Kaiwartya et al., 2016).

Research on VANETs has been consistently ongoing for more than a decade. It was also proposed and presented as a method for traffic congestion control to manage the Intelligent Transportation System (ITS). The aim of VANETs in ITS is to create services that are specifically pertinent to a vehicular context by connecting equipment within vehicles and also the infrastructures (Mchergui, Mulahi & Zeadally, 2022; Lee & Atkison, 2020). VANETs operated independently, without depending on the Internet connection thus effecting the transmission range and scalability (Hichri, Dahi & Fathallah, 2021). Due to the explosion of the technology in the automotive industry, VANETs system needs to be able to handle an environment where the nodes within the network are moving around at high speeds, potentially entering and exiting the network very quickly. However, as more vehicles are connected to the network (heavy traffic), the communication in the Control Channel (CCH) will become increasingly congested, thus affecting the Quality of Service (QoS) such as delay and throughput of data dissemination in the network. As a result, it leads to a longer time consumption in the process of calculating and exchanging information on safety and non-safety messages of the traffic conditions (Hahn et al., 2019; Ferdowsi, Challita & Saad, 2017; Azees, Jegatha Deborah, & Vijayakumar, 2016; Jia & Ngoduy, 2016; Bauza & Gozalvez, 2013b). One way to reduce the congestion in the CCH communication channel is to optimize the network to reduce congestion. However, safety packets with comparable high priority cannot directly benefit from the majority of the optimization of the channel congestion mechanisms implemented in VANETs.

Another critical issue in VANETs is the heightened risk of a broadcast storm, a scenario characterized by excessive packet broadcasting that leads to severe contention and collisions at the link layer (Hanifi & Haghi, 2024; Elias, 2017). This problem occurs when multiple vehicles simultaneously rebroadcast messages, overwhelming the communication channel and degrading overall network performance. To mitigate this issue and enhance communication efficiency, it is essential to equip road users with smarter alternatives. These may include advanced tools, intelligent systems and real-time aids that allow drivers to access relevant traffic information and make informed decisions. Such solutions can help avoid traffic congestion, improve route planning and ensure a more convenient, efficient and stress-free travel experience (Tapas et al., 2023; Dhandala et al., 2017).

## 1.3 Problem Statement

Communication networks are the backbone of ITS since they connect application areas as well as connecting individual components of the system (Hahn et al., 2019). As mentioned in the previous sub-chapter, VANETs was proposed as a method for congestion control to exchange data, improve traffic safety and provide efficient traffic management by disseminating safety and non-safety messages in ITS. The safety messages such as information on traffic congestion, need to be distributed to each neighbouring vehicles immediately with almost no delays since it usually has strong reliability (Hanifi & Haghi, 2024; Elias et al., 2019; Elias, 2017; Darus & Bakar, 2013). The vehicle transmits the message to neighbouring vehicles in the network through protocols to provide informative messages such as traffic congestion notification to the road users. However, when too many vehicles are broadcasting over the same traffic, the network traffic will get dense and it will consume large bandwidth. As a result, the message delivery was vulnerable to packet loss during the transmission. Additionally, the scalability issue in VANETs designs cannot sustain the necessary QoS such as throughput, delays and packet delivery ratio (PDR) as the network grows (Hanifi & Haghi, 2024; Darus et al., 2017). Nevertheless, due to the rapid node numbers, movement and frequent environmental changes, the link connection between the vehicles in VANETs frequently disconnects (Elias, 2017; Rehman et al., 2013). Thus, several congestion control mechanisms to overcome the problem of VANETs have been proposed. The mechanisms include software defined vehicular networking (SDVN) (Jaballah et al., 2019), distributed beacon congestion control (Lyamin, Bellalta & Vinel, 2020), decentralization congestion control (Lyu et al. 2018), vehicular cloud computing, multiplicative rate decreasing algorithm, multi-objective Tabu search and Distributed Fair Transmit Power Adjustment for Vehicular Networks (D-FPAV) algorithm (Torrent-Moreno et al., 2006).

The mentioned congestion control mechanisms have shown through many studies to be efficient in improving the performances of VANETs. Unfortunately, most of the proposed mechanisms are fundamentally an amendment to existing mobile adhoc network (MANET) and routing schemes of VANETs. Thus, it remains unsatisfactory to meet ITS high-performances expectation, such as permanent connectivity (necessary to create route stability), scalability (to satisfy the increasing number of vehicles), high throughput (to compute big cyber-physical data) and heterogeneity (to help interoperability between heterogeneous devices) (Jaballah et al., 2019).

Furthermore, researchers have explored network optimization as an effective approach to overcome the limitations of VANETs. Among various optimization techniques, bio-inspired algorithms, particularly the Particle Swarm Optimization (PSO) algorithm, have been widely adopted to enhance routing performance and message dissemination. PSO has been applied to optimize routing decisions with the objective of achieving faster and more reliable message delivery without interruption. Previous studies have shown that PSO-based routing can enhance vehicular network performance by improving packet delivery efficiency and optimizing routing decisions through the selection of suitable communication paths and forwarder vehicles. These improvements help reduce redundant transmissions and mitigate the influence of rogue or malicious nodes, thereby increasing overall network reliability. Termunikar (2022) reported that the PSO-based approach achieved higher packet delivery ratio, improved throughput, and lower routing overhead compared to conventional VANET routing protocols, particularly under dense traffic conditions. Although reductions in end-to-end delay were observed, delay was not treated as the primary optimization objective but rather evaluated as a secondary performance metric within a general routing efficiency framework.

Moreover, the PSO-based routing approach presented by Termunikar (2022) was evaluated within a VANET-oriented architecture, where optimization was applied at the general network level without explicitly addressing time-critical V2V safety message dissemination in an Internet-enabled IoV environment. Although PSO demonstrated promising improvements in PDR, throughput and routing efficiency, its effectiveness remained constrained by the inherent limitations of VANETs. Particularly, VANETs' communication is highly dependent on network topology and vehicle density, where signal strength degrades near the edge of the transmission range and the control channel becomes increasingly congested as more vehicles participate in the network. This congestion leads to higher contention, increased delay and unstable links, especially in dense traffic scenarios (Hanifi & Haghi, 2024; Muruganet et al., 2020; Samara & Alhmiedat, 2014). As a result, critical V2V challenges such as ultra-low latency requirements, rapid topology changes, and frequent link disruptions were not the primary focus of existing PSO-based VANET studies. These limitations indicate that, despite the promising performance gains achieved through PSO optimization, VANETs are becoming less suitable as a congestion control mechanism in current urban environments where vehicle density and network saturation continue to increase. Therefore, the Internet of Vehicles (IoV) paradigm is proposed to overcome these shortcomings by enabling scalable, Internet-assisted communication and supporting more reliable, low-delay V2V message dissemination under highly dynamic traffic conditions.

IoV network helps in improving intra-vehicle network which means the communication infrastructure among the host vehicle, the neighbouring vehicles, human, cloud and also the Road Side Units (RSUs) (Xu et al., 2018; Chen et al., 2018). In other words, IoV network can deals with a high volume of data. However, despite the advancement and scalability offered by the Internet of Vehicles (IoV), several unresolved challenges still exist as the network continues to grow. One of the primary issues is network congestion, which arises when a large number of vehicles, roadside units, and smart sensors simultaneously participate in data transmission. The massive volume of data exchanged in IoV environments places heavy pressure on the communication infrastructure, particularly in dense urban traffic scenarios, leading to congestion in the network (Karim et al., 2022; Mohamed & AlShalfan, 2021; Hahn et al., 2019; Taie & Elazb, 2016).

Another critical challenge in IoV networks is communication delay, especially in the dissemination of time-sensitive safety messages. Due to high data loads and the increasing number of deployed sensing devices, packets may experience longer waiting times before transmission. This delay becomes more severe during peak traffic conditions, where simultaneous data transmissions compete for limited channel resources (Zamrai, 2021; Royyan et al., 2018; Ferdowsi, Challita & Saad, 2017). Such delays can significantly reduce the effectiveness of safety applications that require near-instantaneous message delivery.

Furthermore, when the transmitted packet load exceeds the available buffer capacity during dense traffic conditions, the communication channel becomes flooded with packets. This situation leads to packet collisions and buffer overflow, increasing the likelihood of packet drops during transmission. As a result, the overall reliability of the IoV network is compromised, particularly in highly dynamic and congested environments (Royyan et al., 2018; Ferdowsi et al., 2017).

Consequently, these conditions lead to a degradation of Quality of Service (QoS) in IoV networks. Key performance metrics such as throughput, PDR and delay are adversely affected. Reduced throughput limits efficient data dissemination, lower PDR indicates unreliable communication, and increased delay undermines the timeliness of safety-critical messages. These QoS degradations highlight the need for effective congestion control and optimization mechanisms in IoV networks (Karim et al., 2022; Panimalar & Jacob, 2020; Royyan et al., 2018).

As a solution to overcome the stated problem, this research aims to enhance the existing IoV network architecture by integrating a bio-inspired optimization algorithm to address the issue of network congestion. Previous studies have shown that bio-inspired algorithms can effectively reduce congestion and improve the efficiency of communication channels in vehicular networks (Karim et al., 2022; Javadpour et al., 2021; Murugan et al., 2020). However, for such optimization techniques to be meaningfully evaluated, it is essential to identify consistent QoS parameters that truly reflect network performance. Although QoS can be measured through various metrics, there has been limited emphasis on standardizing the key parameters that should be used across different vehicular networks. Therefore, this research evaluates the performance of the optimized IoV network using three critical metrics which are throughput, PDR and delay, as they directly indicate efficiency, reliability and timeliness of communication.

## 1.4 Research Question

There are several research questions (RQs) that can be inferred from this research problem. The central research question can now be stated as follows:

i) How can the IoV network be optimized?
ii) What are the parameters for optimization of the IoV network?
iii) What are the outcomes of the performance metrics of the IoV optimization network?

## 1.5 Research Objectives

In line with the identified research gaps, the objectives of this research are outlined as follows:

a) To propose a conceptual optimized IoV network in urban city scenario.

b) To identify the optimization parameters in the IoV network communication that directly impact congestion and Quality of Service (QoS).

c) To evaluate the parameters on the IoV network based on Particle Swarm Optimization algorithm that can reduce delay, increase the throughput and the packet delivery ratio.

## 1.6 Contribution of the Study

The primary contribution of this research is the development of an optimized IoV network architecture tailored for efficient delivery of safety messages in high-density vehicular environments. The proposed solution aims to enhance overall network performance by increasing throughput and PDR, while simultaneously reducing delay thereby improving the reliability and responsiveness of safety-critical communications. The specific contributions of this work to the existing body of knowledge are as follows:

1. The development of an optimized IoV network based on Particle Swarm Optimization (PSO) algorithm for safety packets delivery in city environment.
2. A simulation framework has been established for the purpose of the evaluation of IoV network mobility model for city scenario to ascertain realistic communication between vehicles (V2V).
3. The implementation of delay as the objective function of the optimized IoV network.
4. The evaluation of the performance based on measurements of significant QoS metrics in vehicular network such as increment in throughput and PDR and decrement in packet delay.

## 1.7 Motivation

The "Internet of Things" has gotten a lot of attention. In terms of future orientations, the current Gartner Hype Cycle for Emerging Technologies 2016 places Autonomous Vehicles practically at the "Peak of Inflated Expectations." In this light, IoT technology in transportation and vehicular networks, also known as IoV technology, is a current trend that business strategists, chief innovation officers, research and development leaders, entrepreneurs, global market developers, and emerging-technology teams should consider when developing emerging-technology portfolios. According to Gartner, it is one of the technologies that will provide a significant competitive advantage over the next five to ten years. According to Gartner, 70 percent of all auto-related customer contacts will be digital by 2020.

It is also supported by the Global Market Insights 2016 report, which states that "increasing traffic efficiency with traffic congestion control, which results in reduced travel time, fuel consumption, and thus contributes to improving the environment, is likely to positively impact industry growth over the forecast period." (Global Market Insights, 2016).

Apple, Google Inc., BMW Group, Daimler AG, General Motors, Toyota, Volkswagen group, Delphi, Autotalks Limited, eTrans Systems, Honda, Volvo, Audi, Denso Corp, Qualcomm, Savari INC, and Kapsch's TrafficCom are among the prominent participants with vehicle-to-vehicle communication market share. Furthermore, mobility data traffic is predicted to generate around 0.6 exabytes per month by 2020, which is equivalent to nearly nine percent of total US cellular data traffic (Smud, Ninan, Ramachandran, & Moceri, 2017). The scope of future mobility and vehicular in the IoV network is visibly escalating upwards, necessitating additional research. Figure 1.1 shows the trend of the emerging technologies.

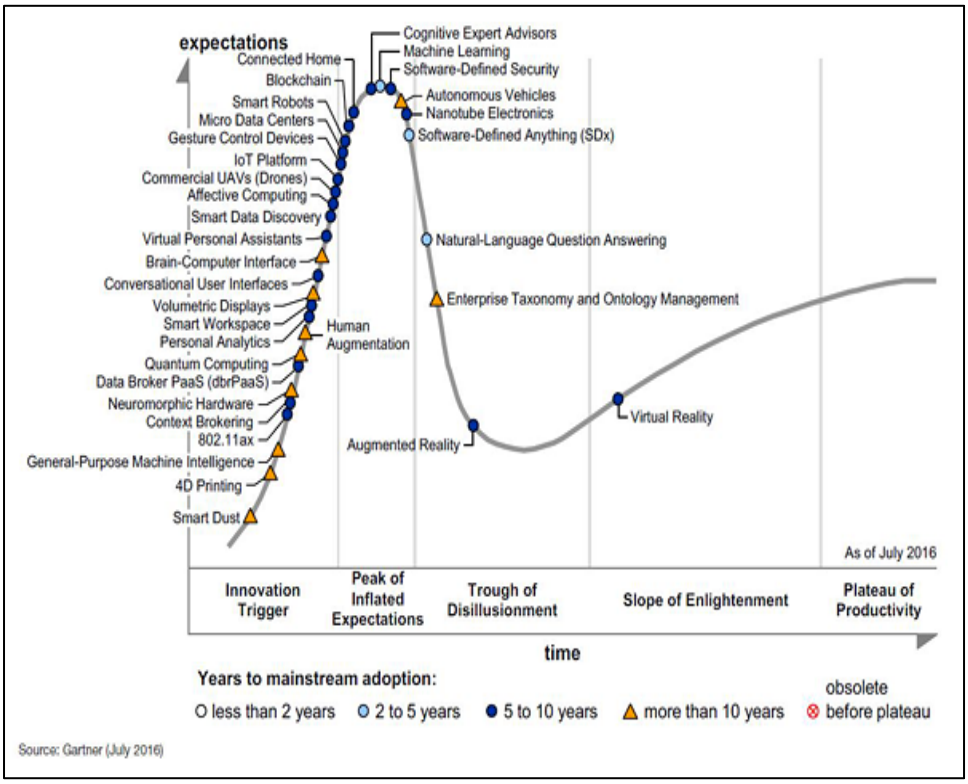



Figure 1.1 Gartner's 2016 Hype Cycle for Emerging Technologies

Figure 1.1 above shows Gartner's 2016 Hype Cycle for Emerging Technologies, which illustrates the maturity and adoption expectations of various innovations over time. This trend is reflected in national strategic frameworks as well. The Malaysia Digital Economy Blueprint which was launched on 19th February 2021, highlights the widespread adoption of digital technologies as a direct outcome of the Fourth Industrial Revolution (IR4.0). This indicates a conjunction between global technological foresight and national digital transformation agendas. Emerging technologies such as Internet of Things (IoT), blockchain, Artificial Intelligence (AI), cloud computing, Big Data, Virtual Reality (VR) and Augmented Reality (AR) are currently being actively implemented to improve the Malaysia digital economy. It is expected that these technologies will benefit the country in terms of society, business and also the government. Moreover, the blueprint also itemised its plans to achieve the vision of Malaysia to become a regional leader in the digital economy, as well as attain inclusive, responsible and sustainable socioeconomic development (Malaysia Digital Economy Blueprint, 2021). Figure 1.2 shows the domains of the Industrial Revolution 4.0 (Malaysia Digital Economy Blueprint, 2021) whereas Figure 1.3 demonstrates the Malaysia's digital economy journey from the year of 1996 to 2019 (Malaysia Digital

Economy Blueprint, 2021).

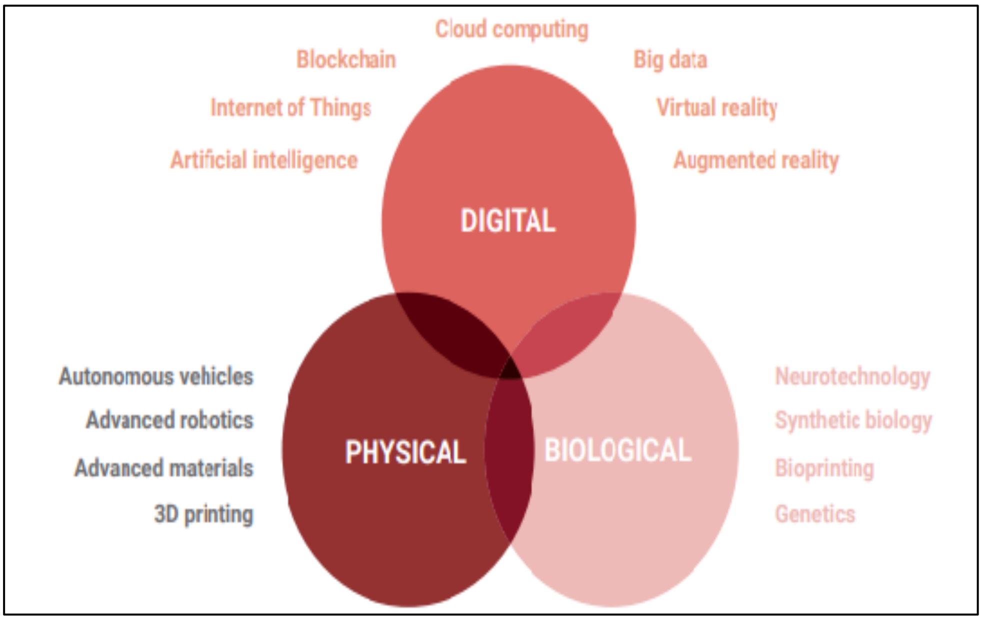


Figure 1.2 Domains of IR 4.0 Technologies

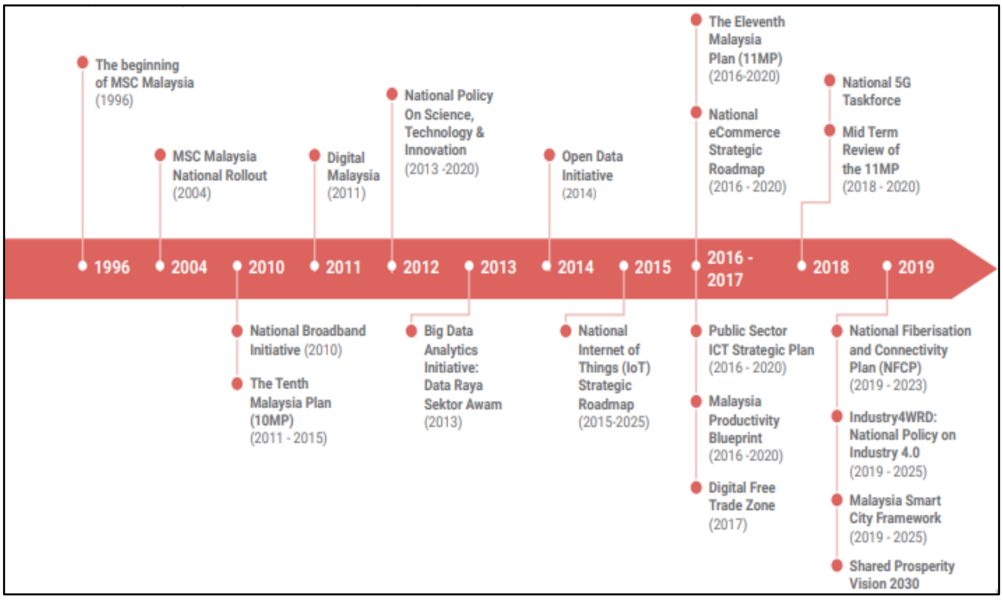


Figure 1.3 Malaysia's Digital Economy Journey 1996-2019

As highlighted in Figures 1.2 and 1.3, Malaysia's digital economy blueprint places strong emphasis on IR 4.0 technologies, including IoT, AI, and big data, which serve as enablers for smart mobility. Within this context, the Internet of Vehicles (IoV) emerges as a key application area under the IoT domain, supporting Malaysia's transition towards intelligent transportation and smart city ecosystems. However, despite these advancements, congestion control in IoV communication remains a major challenge that can hinder reliable data dissemination and affect safety-critical applications. To address this gap, Figure 3.1 in chapter 3 outlines the proposed IoV research framework developed in this study, which integrates bio-inspired optimization to enhance network performance. Furthermore, according to the Malaysian Institute of Economic Research's (MIER) newest estimate, 5G implementation might produce RM12.7 billion for Malaysia's digital economy between 2021 and 2025. During this time, the positive impact included the creation of over 39,000 additional job opportunities.

## 1.8 Research Scope

The intention of this research is to implement IoV network optimization for the purpose of congestion control in ITS, contributing to the Smart City and Smart Mobility initiative. Focusing on this goal, the scope of the research covers on the areas of traffic congestion and the adaptation of the IoV network optimization to enhance the process of safety-based data transmission.

In this research, the vehicle-to-vehicle (V2V) communication is considered for the urban vehicular scenario. However, there is no physical vehicle or urban environment is arranged for this research. The scenario of the simulation selected is the city centre of Kuala Lumpur, Malaysia where this city is currently exposed to frequent traffic congestion as per statistic mentioned in the previous sub-chapter. Obstacles in urban areas such as buildings, which usually barricade the transmitted signals, were not considered.

The proposed optimized IoV network is developed using two well-established simulators for vehicular network which are SUMO (Simulation of Urban Mobility), a road traffic simulator and OMNeT++ (Objective Modular Network Testbed in C++), an event-based network simulator. Both simulators are integrated through Veins (Vehicles in Network Simulation). It is an open-source framework that is used to execute simulations of vehicle networks based on two simulators mentioned. As for the optimization, the proposed optimized IoV network is using Particle Swarm Optimization (PSO) algorithm. The algorithm is used to optimize the data transmission rate, utilizing delay as the objective function in the algorithm. The performance evaluation of the network is based on three QoS metrics which are throughput, delay and PDR. In this study, the nodes interact with one another and share road information focusing on safety messages in a friendly environment where privacy and security issue are not considered in the communication of data packet. The interaction between the vehicles and the cloud is assumed as clear as there is no interference during the simulations. The packets is also assumed to have similar priority in the IoV network.

## 1.9 Significance of the Study

This research aims to explore the suitable approach to reduce traffic congestion contributing to the ITS for Transportation and Mobility initiative in Kuala Lumpur, Malaysia. In the light of worsening traffic congestion in many urban cities due to rapid development causing serious environmental effects, many initiatives have been proposed to mitigate this problem. Vast research and development in many developed and developing countries in the United States, United Kingdom, Europe and Asia are in pursuit for addressing this problem by means of technological advancement for better social, economic and environmental benefits. In order to avoid congestion, it is very important for a vehicular network to own the capability of disseminating messages without any obstacle. If this issue is neglected, the node and its neighboring vehicles may experience a long waiting time because of the possibility of the network becomes congested. As a result, the QoS will be affected. The transmission rate or called throughput of the network will automatically decrease when the delay increases. The development of optimized IoV netwok is expected to prevent traffic congestion in disseminating safety messages, thus ensure better data dissemination. Besides, this research also aimed to add more knowledge to the existing body of knowledge on the subject matter.

## 1.10 Thesis Outline

The remaining chapters of this thesis are organized as follows.

Chapter 2 presents a comprehensive literature review that explores the key aspects of the Internet of Vehicles (IoV) domain. This includes an overview of its foundational concepts, current architectural models and the primary challenges faced by existing IoV networks, particularly issues related to congestion and scalability. The chapter also discusses various congestion control techniques that have been proposed in recent studies. By the end of the chapter, the research gaps identified in the literature are synthesized to justify the need for the proposed congestion control mechanism introduced in this study.

Chapter 3 describes the research methodology adopted for this work. It begins with the problem formulation, which is developed based on insights gained from the literature review. This is followed by a detailed explanation of the simulation setup, including the design and configuration of the IoV network. The chapter concludes by outlining the implementation strategy for the proposed PSO algorithm within the IoV framework, highlighting how the algorithm is tailored to address congestion control issues in vehicular networks.

Chapter 4 details the design and implementation of the optimized IoV network in a realistic urban city scenario. The performance evaluation of the network is conducted using the OMNeT++ simulator. The simulation results demonstrate that the optimization approach significantly enhances the dissemination of safety-related applications, particularly in high-density traffic environments, thereby validating the effectiveness of the proposed method.

Chapter 5 focuses specifically on the optimization strategy applied to improve the dissemination of safety packets with similar priority levels. The chapter explains how the PSO-based optimization algorithm resolves network congestion issue, thereby improving communication efficiency. The simulation outcomes further support the claim that the proposed method effectively addresses the challenges associated with safety message delivery in the network.

Chapter 6 concludes the thesis by summarizing the main findings and contributions of the research. It reflects on the key achievements, recaps the significance of the proposed approach and offers recommendations for future work, particularly in enhancing adaptive congestion control mechanisms and real-world deployment of optimized IoV network.

# CHAPTER 2
# LITERATURE REVIEW

## 2.1 Introduction

This chapter provides an introduction to the key areas underpinning the main research in the thesis. The main focus of this research is to design and develop an efficient optimization of IoV network as a method of congestion control. In this chapter, the domain which traffic congestion is discussed in detail. Next, the summarization of two major vehicular network element as a method of congestion control is presented. The networks include the vehicular adhoc networks (VANETs), Internet of Things (IoT) and Internet of Vehicles (IoV).

In a nutshell, this chapter investigates the implementation towards addressing the current traffic congestion issues raised in VANETs and current implementation of IoV network as a solution of VANETs deficiencies. Subsequently this chapter review and discusses the IoV network, which includes the infrastructure, network and communication module, mobility design and the congestion control issues raised in the current IoV network management. Nevertheless, this chapter also provide a thorough discussion on the optimization and application as a solution and related literature and research to discuss the extent of the limitation and in highlighting the research issues and gaps that need to be addressed. In particular, Figure 2.1 illustrates the research challenges in developing an efficient optimized IoV network shown in coloured box aims to increase the reliability and disseminating the safety-based packets on time without congestion.

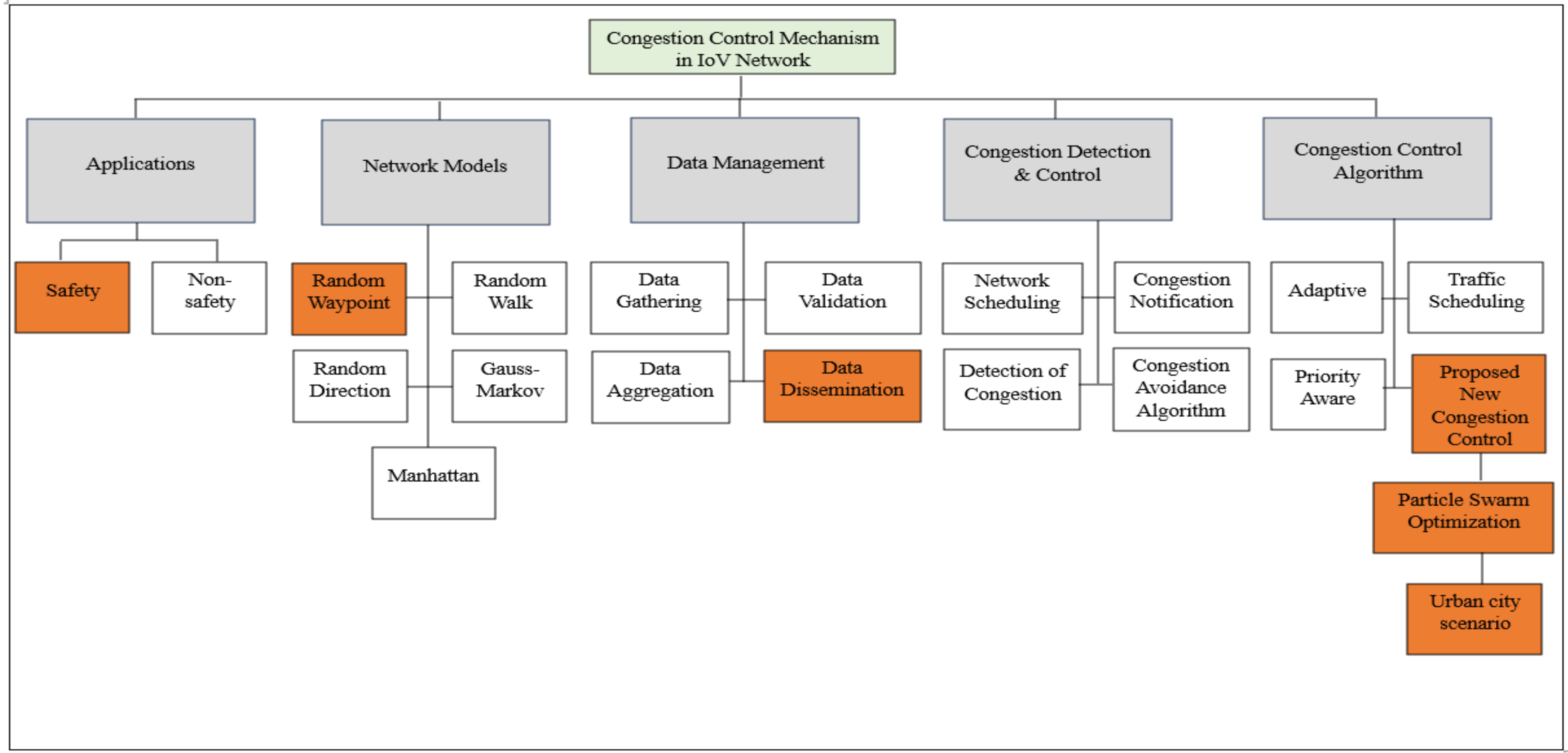



Figure 2.1 Taxonomy of Literature Review

## 2.2 Traffic Congestion

The lifestyle of the people has changed substantially during the last few decades as a result of transportation. Developed countries now have the ability to think differently because of transportation. An effective global transportation system has visible consequences that can be observed in anything from the movement of goods to daily commutes. As a result of the development of technology, transportation facilities have rapidly increased throughout the 20th century. Moreover, in the 21st, things have developed enormously and to a point where they appear to be beyond human control. Although life has become easier with the development of speedier ways of transportation and the ease of automobile ownership, the environment is paying a high price for this. The modern cars is produced with a wide variety of electronic control units, such as power steering, rear-view cameras, brake systems, etc. The vehicle industry is no longer mechanical in today's world. It is mechanised and computerised instead (Ata et al., 2019). Thus, ITS is introduced to intelligently and efficiently manage the traffic congestion problem.

The main issue that practically all governments in the world are dealing with is vehicular congestion (Suhaimi, 2024; Ali et al., 2019; Hatim et al., 2018). The major nations of the world including Malaysia, have experienced serious effects from congestion as it is growing day by day. It is characterised as the result of an uneven traffic flow when the number of cars circulating in a certain area increases, exceeds the maximum capacity of the road, especially during peak hours (typically during working or office hours, which are the morning and evening). In other words, it is described by slower speeds, longer excursion times, and expanded vehicular queueing. The main factors that contribute to this event are uncontrolled advancement of the automotive sector, lack of urban transportation planning and weather conditions (Bakar et al., 2019; Ali et al., 2019; Elias et al., 2019).

It is necessary to continuously obtain data about the state of the transport network in order to maintain an efficient transportation infrastructure and plan for existing and future needs. Therefore, gathering current and reliable traffic information is a crucial responsibility for traffic authorities and other responsible parties in order to reduce congestion (Bakar et al., 2019).

### 2.2.1 Intelligent Transportation System (ITS)

ITS can be described as the advancement of technology towards smart cities solution. It involves a series of application systems especially for transportation services such as vehicles management system (synchronized traffic lights), automatic license plate recognition system and traffic signal control system (Chen et al., 2018). In order to meet the demands of the transportation development revolution, the common integration of sophisticated sensing, communication, and information technologies are crucial for enhancing the effiectiveness, safety, and efficiency of transportation systems. Vehicles and transportation infrastructure must be outfitted with intelligent sensors that can gather and interpret a diverse range of data about each vehicle, its occupants, and its environment (Ferdowsi et al., 2019). ITS is expected to be able to deliver accurate and timely traffic scenario (Zhang et al., 2023). Table 2.1 shows the generation of the ITS and Figure 2.2 illustrates the overview structure of ITS.

Table 2.1
Generation in ITS (Cui & Lei, 2023)

| **Generation** | | **Feature(s)** |
|---|---|---|
| First generation | Early ITS | Basic infrastructure improvements and traffic management such as automated traffic signals and route guidance. |
| Second generation | Advanced ITS | It involve more sophisticated technologies. Traveler information systems, electronic toll collection, and integrated traffic management were introduced. |
| Third generation | Connected and Automated Vehicles | There are widespread adoption of connected vehicles and autonomous driving during this generation. The data collection, analysis, and decision-making emphasizes on real-time basis to optimize traffic flow and improve safety. The integration of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication were observed. |
| Fourth generation | Intelligent Mobility | This generation of ITS introduces integrated and intelligent transportation networks that can adapt to dynamic conditions and user needs by incorporating AI, big data analytics, and advanced communication technologies |

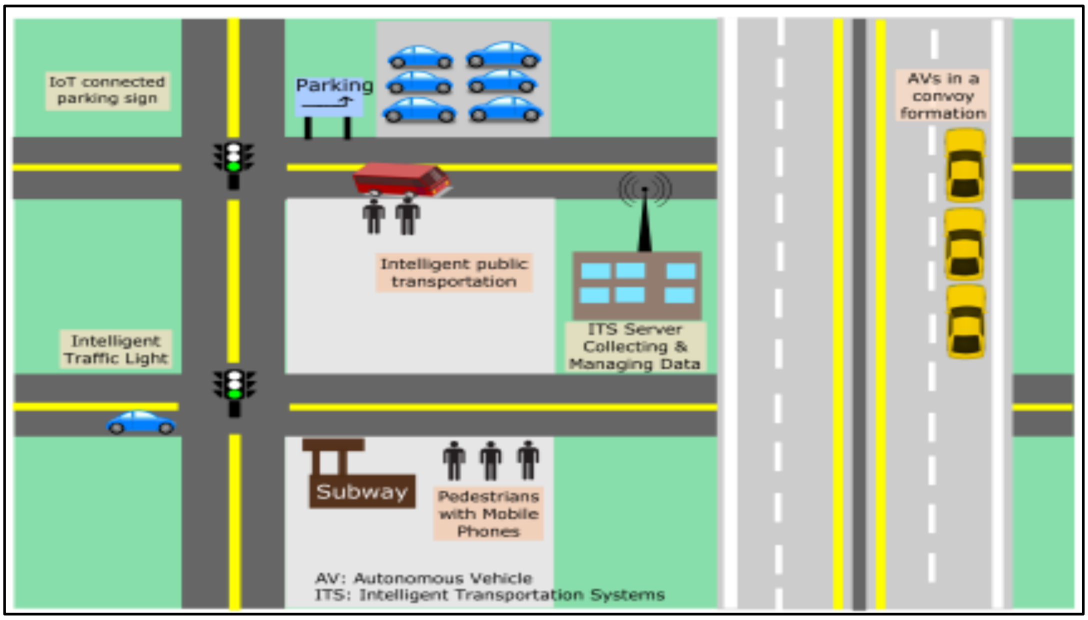



Figure 2.2 The Architecture of ITS (Hanh et al., 2019)

Figure 2.2 above illustrates a conceptual framework of an ITS, showcasing the integration of advanced technologies to enhance urban mobility, safety and efficiency. Central to the system is the ITS server, which functions as a data hub, collecting and managing real-time information from various sources across the transportation network. Key components include Internet of Things (IoT) connected parking signs that monitor and communicate parking availability, thereby reducing congestion and improving driver experience. Intelligent traffic lights are depicted at intersections, representing adaptive signal control systems that respond dynamically to traffic conditions. Public transportation is enhanced through smart buses equipped with tracking and scheduling technologies, while subway infrastructure supports multimodal connectivity. The presence of pedestrians with mobile phones highlights the role of user-generated data in shaping responsive mobility services. Additionally, autonomous vehicles traveling in convoy formation demonstrate V2V communication and coordinated automation, contributing to safer and more efficient highway travel. Collectively, these elements illustrate how ITS leverages data, connectivity, and automation to create a cohesive and responsive urban transportation ecosystem.

While the conceptual framework of an ITS demonstrates significant potential in transforming urban mobility through data-driven and automated solutions, its practical implementation remains fraught with technical challenges. The integration of diverse components ranging from IoT-enabled infrastructure to autonomous vehicles requires the continuous transmission and processing of vast volumes of sensor data. However, industry and academic researchers continue to face a number of critical obstacles that prevent ITS development from moving further. Due to the enormous number of mobile sensors in an ITS, the transmission of all of the sensor measurements to a remote cloud can lead to significant delays, network congestion and computing overload (Zhang et al., 2023; Ferdowsi et al., 2019). This is unacceptable for an ITS since any delayed decision in the system might cause traffic congestions, travel delays and accidents.

Another issue discovered in the current ITS is the process of gathering and labeling of the extensive and varied datasets from actual traffic situations. It is time-consuming and requires tremendous effort. Furthermore, human annotators are prone to make mistakes or inconsistencies while classifying the traffic data manually. Moreover, environmental conditions significantly impact the data collection accuracy. The factors such as poor illumination, unpredictable weather conditions and obstructions from other vehicles can make it difficult for both human observers and also automated systems to accurately label vehicles, pedestrians and road signs (Zhang et al., 2023; Talib et al., 2017; Targe & Satone, 2016).

ITS has already become a global phenomenon, which aims to increase the benefits of the public and, implicitly, private sector. The design of the ITS is complex since the systems consist of large structures with a reliable number of subsystems and components. The subsystems include user, vehicle, infrastructure, communication and control and management (Cui & Lei, 2023). Table 2.2 below shows the details on the subsystems of ITS.

Table 2.2
Subsystems of ITS

| **Subsystem** | **Description** | **Application** |
|---|---|---|
| User | This subsystem includes the interaction between ITS and different types of users, including drivers, passengers, pedestrians, and system operators. It provides real-time information, navigation support, and decision-making assistance. | i) Traveler Information Systems<br>Real-time updates on traffic conditions, public transport schedules, and weather. |
| | | ii) Navigation & Route Guidance<br>GPS-based route optimization and congestion avoidance. |

| | | |
|---|---|---|
| | | iii) Emergency & Safety Alerts<br>Collision warnings, pedestrian alerts, and roadside assistance. |
| Vehicle | The vehicle subsystem includes all technologies embedded within vehicles to enhance safety, efficiency and connectivity. | i) Advanced Driver Assistance Systems (ADAS)<br>Lane departure warnings, adaptive cruise control and automatic emergency braking. |
| | | ii) Autonomous & Connected Vehicles<br>Self-driving capabilities and vehicle-to-everything (V2X) communication. |
| | | iii) Onboard Diagnostics & Monitoring<br>Sensors that track vehicle performance, emissions, and maintenance needs. |
| Infrastructure | This subsystem includes physical infrastructure integrated with smart technologies to support traffic management and safety. | i) Roadside Sensors & Cameras<br>Traffic monitoring devices for congestion detection and law enforcement. |
| | | ii) Intelligent Traffic Signals<br>Adaptive traffic lights that adjust based on real-time demand. |
| | | iii) Smart Parking Systems<br>Automated parking availability detection and guidance. |
| Communication | ITS relies on seamless communication between vehicles, infrastructure, and control centers to ensure efficient operation. | i) Vehicle-to-Vehicle (V2V) Communication<br>Data exchange between cars to prevent collisions and optimize traffic flow. |
| | | ii) Vehicle-to-Infrastructure (V2I) Communication<br>Interaction between vehicles and road infrastructure for traffic signals and road condition updates. |

| | | |
|---|---|---|
| | | iii) Cloud & Edge Computing<br>Real-time data processing and decision-making through IoT and AI integration. |
| Control and management | This subsystem is responsible for coordinating and optimizing ITS operations, using data-driven strategies to enhance transportation services. | i) Traffic Management Centers (TMCs)<br>Centralized systems that monitor and control traffic signals, congestion management and emergency response. |
| | | ii) Public Transport Management<br>Fleet tracking and scheduling for buses, trains, and other transit services. |
| | | iii) Law Enforcement & Incident Management – Automated toll collection, speed enforcement, and accident response coordination. |

As shown in Table 2.2, each subsystem in ITS plays a crucial role in ensuring safe, efficient, and sustainable transportation. The integration of user, vehicle, infrastructure, communication and control subsystems enables seamless mobility and enhances the overall transportation experience. Since ITS aims to create better traffic management and allow users to better informed, stay safe and coordinated in the vehicular network, the centralization of ITS centres around Malaysia is seen as one of the strategies to alleviate traffic congestion (Musa et al., 2018). Recently, there are some ITS operated and upheld by several agencies in this country. For instance, The Kuala Lumpur City Hall (DBKL) has built the Integrated Transport Information System (ITIS), which is used to monitor and supervise traffic flow in Kuala Lumpur and the Klang Valley (Musa et al., 2018). On the other hand, the Malaysian Highway Authority (MHA), which is part of the Malaysian Ministry of Works (MOW), operates a traffic management centre (TMC) on all tolled highways to gather and manage traffic data. Meanwhile, PLUS Malaysia Berhad introduced their Traffic Monitoring Center (TMC) where the purpose of the centre is to accumulate and transmit real-time traffic data for effective traffic management, as well as to coordinate support for highway users (PLUS, 2020). PLUS also introduce and manage several ITS equipment such as Variable

Message Sign (VMS), Automatic Vehicle Detection System (AVDS), Close Circuit Television (CCTV) and GPS.

Previously, Vehicular Adhoc Networks (VANETs) were introduced as a key enabler within ITS to address the growing challenges in road traffic management. The primary objective of VANETs is to enhance traffic safety, improve traffic flow efficiency and create a more comfortable and informed travel experience for both drivers and passengers (Elias et al., 2019). By enabling real-time communication between vehicles and infrastructure, VANETs facilitate timely dissemination of critical information such as accident alerts, traffic congestion updates and road hazard warnings.

Given their crucial role in modern transportation systems, it is essential to explore the underlying architecture, communication models and key components that show the effectiveness of VANETs. The following section investigates deeper into the core aspects of VANETs, including their network topology, communication types and the technologies that support seamless connectivity and reliable data exchange.

## 2.3 Vehicular Adhoc Networks (VANETs)

VANETs plays a significant role in establishing seamless communication and information interchange between the vehicles on the roads and the RSUs in ITS. It is based on IEEE 802.11p standard and supports real-time data exchange, thus enhance traffic management, road safety, and driver assistance services. VANETs significantly contribute to the efficiency, safety, and intelligence of modern transportation systems by providing timely information on traffic conditions, accidents and road hazards (Pamungkas et al., 2019).

In terms of architecture, VANETs utilize vehicles as mobile nodes that continuously move and interact within a defined communication range. These vehicles are typically equipped with on-board units (OBUs), sensors, GPS modules, and wireless transceivers, enabling them to send, receive, and relay information dynamically across the network. VANETs inherit several characteristics from Mobile Ad Hoc Networks (MANETs), such as operating in a wireless environment, functioning without fixed infrastructure, for example decentralized or limited centralized control and being composed of mobile nodes that self-organize to form temporary networks (Elias et al., 2019; Eze, 2016; Taherkhani, 2015; Truong, 2015; Liang, 2015; Dua, 2015).

However, VANETs distinguish themselves through unique features tailored to vehicular environments. These include high mobility, as vehicles move at varying speeds and directions; rapidly changing topology, which requires robust and adaptive routing protocols and dense network environments, especially in urban or highway scenarios, where a large number of vehicles may attempt to communicate simultaneously. Additionally, the communication in VANETs must account for constraints such as signal fading, intermittent connectivity and varying communication delays.

VANETs can be classified into two main applications which are safety and non-safety applications (Sharma et al., 2021; Elias et al., 2019; Elias et al., 2016; Taherkhani, 2015). The objective of safety applications is to prevent road accidents by sending useful information to the road drivers connected in the network. Due to the high speed of vehicles on the roads, drivers may not alert with the risky situations. The aim of safety application is to provide lifesaving support to road drivers. For instance, when the safety applications send emergency signal such as the notification of road accident to the vehicles, the road drivers can decrease their speeds towards the accident spot, thus avoiding another accident. Moreover, road drivers can make a turnover or find alternative path to avoid traffic congestion during peak period, which can prevent traffic congestion. Safety applications use safety messages that can be clustered into beacon or periodic messages and emergency messages. The beacon messages are often disseminated between the vehicles in the network to transfer or exchange the information about the neighbouring vehicles. However, the emergency messages are only sent when an unusual event occurs such as car accidents. Applications such as crash warning and emergency election break lights, used the emergency message whereas information about the vehicle such as position, speed, and route are included in the beacon message. There are some other applications such as the intersection collision warning, low bridge warning, and cooperative collision warning are also included and categorized as beacon messages (Elias et al., 2019; Elias et al., 2016; Taherkhani, 2015)

On the other hand, the non-safety applications it is rather useful in ensuring traffic convenience and efficiency when the drivers are travelling on the road (Elias et al., 2019). The purpose of this application is to provide information on the traffic flow, stress-free driving and point of interest (POI) (Elias et al., 2019; Elias et al., 2016; Taherkhani, 2015). Non-safety applications of VANETs should provide unified internet connectivity to road users since there is a substantial need for people who traveling with vehicles attached to the internet. The example of safety and non-safety VANET applications can be seen in Table 2.3.

Table 2.3
The Comparison of Safety and Non-safety Applications (Elias et al., 2019)

| **Category** | **Application** |
|---|---|
| Safety | Traffic violation |
| | Curve speed warning |
| | Emergency vehicle warning |
| | Left turn assist |
| | Stop sign assist |
| | Co-operative forward collision |
| | Lane change warning |
| | Pre-crash sensing or warning (accident) |
| | Emergency brake lights |
| | Collision risk warning |
| | Hazardous location notification |
| | Control loss warning |
| | Traffic and route optimization |
| Non-safety | Infotainment |
| | Payment services |
| | Point of Interest (POI) |
| | GPS Update |

In reference to Table 2.3, safety applications demonstrate significant importance in mitigating traffic congestion. These applications including accident detection, collision avoidance, lane departure warnings and emergency vehicle alerts, effectively reduce congestion and improve traffic flow through timely responses and preventive actions. Safety-focused technologies therefore play a crucial role in maintaining steady vehicle movement via efficient communication channels, minimizing road disruptions and enhancing the overall performance of transportation networks.

Communication is the key component in the architecture of VANETs, in order to support effective transmission of safety and non-safety messages. Typically, two main communications in VANETs are vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I).

### 2.3.1 Types of Communications in VANETs

In VANETs, V2V communication enables direct wireless data exchange among nearby vehicles, facilitating rapid dissemination of safety and mobility information. Complementing this, V2I communication connects vehicles to Roadside Units (RSUs), allowing access to broader traffic management systems and external networks. The integration of V2V and V2I communication forms the backbone of ITS, supporting real-time data sharing, cooperative decision-making and proactive safety measures. Together, these communication modes significantly enhance road safety, traffic efficiency and the overall driving experience.

Sections 2.3.1.1 and 2.3.1.2 further elaborate on the mechanisms, functionalities and advantages of V2V and V2I communications, respectively, highlighting their roles within the IoV architecture in enabling intelligent, reliable and cooperative vehicular networks.

#### *2.3.1.1 Vehicle-to-Vehicle (V2V) Communication*

V2V communication can have beneficial impact in enhancing traffic throughput and safety. Each vehicle is considered a node in the network in V2V communication. It is a source, a destination and at times routers that sends, receives and disseminate information to or between other participating vehicles on the road (Mansor, 2017; Rawat & Yan, 2010). For instance, if V2V communication were to be used for an emergency lane change plan, then one can reduce the spacing between vehicles while avoiding an obstacle (Darbha et al., 2017). This exchange of information between vehicles is made possible with the Wireless Access in Vehicular Environment (WAVE) through an On-Board Equipment (OBE) through a fixed radio channel. The communication mode is called WAVE Short Message Protocols (WSMP) mode that enables the information exchange (Mansor, 2017; Ahmed et al., 2013). Figure 2.3 below illustrates the structure of VANETs.

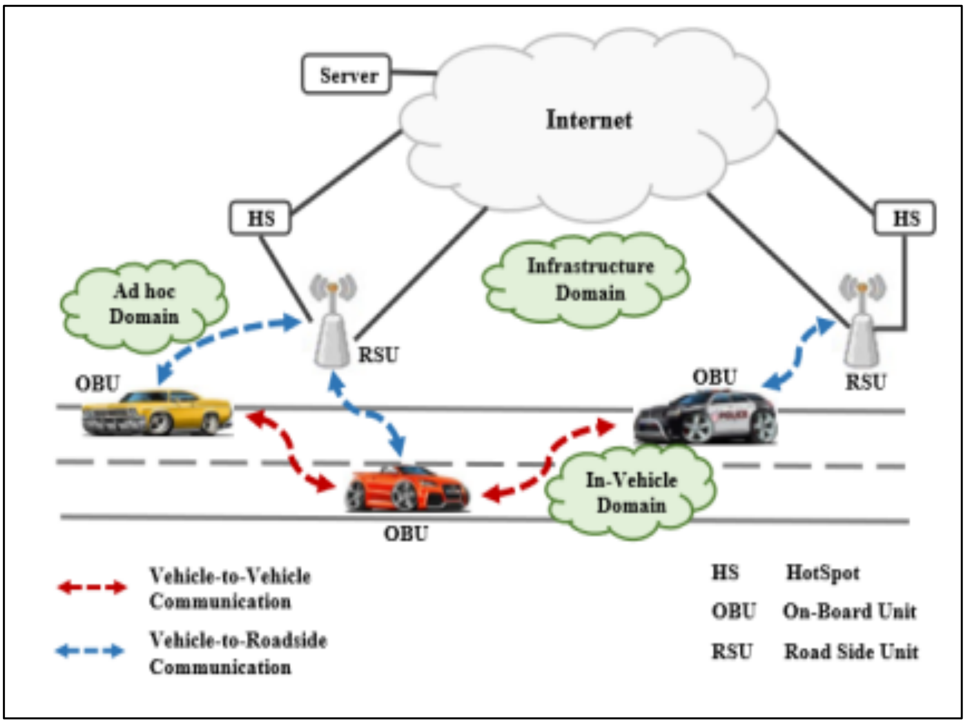



Figure 2.3 The Structure of VANETs (Elias et al., 2019)

Figure 2.3 illustrates V2V communication, where vehicles are interconnected wirelessly through embedded On-Board Units (OBUs). Each OBU functions as a wireless communication platform that enables direct data exchange among vehicles within proximity, forming a short-range ad hoc network based on IEEE 802.11p standards. Through this connection, vehicles can broadcast and receive critical safety information such as speed, position, and braking status in real time. This direct communication allows vehicles to cooperate dynamically, detect potential collisions, and coordinate maneuvers without relying on external infrastructure. Consequently, V2V communication enhances situational awareness, reduces accident risks, and improves overall traffic efficiency by ensuring timely information dissemination among vehicles (Elias et al., 2019; Jain, 2018; Darus et al., 2017; Dua et al., 2015).

#### *2.3.1.2 Vehicle-to-Infrastructure (V2I) Communication*

In V2I communication, the roadside infrastructure such as lamp posts and road signs are also equipped with a Road Side Equipment (RSE) that connects the vehicles or nodes to the access network before channelling them to the core network. OBEs and RSEs can share data and control information, and RSEs are connected to a wide area network (WAN), allowing information from the vehicle to be transmitted to the internet as well (Mansor, 2017; Yan, Wang, & Li, 2016). Figure 2.4 shows the V2I communication in VANETs.

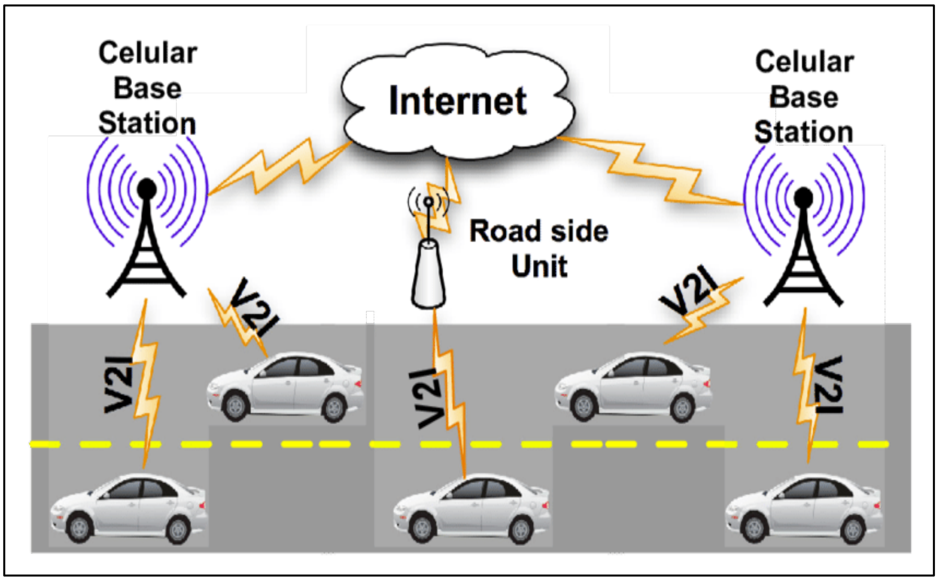



Figure 2.4 V2I Communication (Ullah, 2016)

Figure 2.4 illustrates V2I communication, where vehicles equipped with OBUs interact wirelessly with RSUs or other fixed infrastructure components. Through this connection, vehicles can access broader traffic information such as signal timings and road conditions, which are transmitted from centralized traffic management systems. The RSUs act as intermediaries that collect, process and relay data between vehicles and the central network, enabling coordinated control of traffic flow and improved situational awareness. V2I communication therefore complements V2V by extending the awareness of the vehicle beyond its immediate surroundings, supporting efficient traffic regulation, enhanced safety and optimized route planning in ITS (Elias et al., 2019; Darus et al., 2017).

While VANETs, through V2V and V2I communication, offer substantial benefits in enhancing traffic congestion management, autonomous driving coordination and driving comfort, their real-world implementation still faces several technical and practical challenges. The highly dynamic nature of vehicular environments, along with factors such as unpredictable node mobility, network scalability and signal interference, can affect the reliability and consistency of data transmission. Moreover, issues related to latency, security, data privacy and infrastructure deployment present significant barriers to the seamless operation of VANETs in large-scale ITS applications.

Understanding these limitations is crucial for identifying areas that require further research and optimization. The next chapter discusses these challenges in detail, shedding light on the inherent constraints of VANETs and highlighting the need for more adaptive, robust, and intelligent solutions to ensure their effectiveness in future transportation systems.

### 2.3.2 The Limitations of VANETs

VANET technologies support a wide variety of applications, ranging from traffic safety features such as collision and traffic violation warnings to infotainment services, including real-time navigation, internet access, and multimedia streaming (Elias et al, 2019; Taherkhani, 2015). These diverse applications rely heavily on the underlying communication capabilities and dynamic architecture of VANETs. While VANETs are recognized for their unique advantages such as high mobility, rapid topology changes, and real-time data exchange, their conventional implementations are often constrained by limited scalability and small network sizes. These limitations can degrade the performance and reliability of VANET-based applications, especially in densely populated urban areas or high-speed environments where robust and large-scale communication is essential.

The mobility constraints and the number of connected vehicles is the issues raised in VANETs make it unstable. The feature of dynamic topology cause VANETs to be vulnerable towards excessive data loads and it get easily congested. The nodes competing in getting through the network to obtain information (Dua et al., 2015; Morgan, 2014). QoS metrics such as delay and packet loss are considered to guarantee the reliability and safety messages dissemination of the VANETs. Thus, there was a significant need for congestion control strategies in VANETs to deliver the safety messages to road users (Sharma et al., 2021; Taherkhani, 2015; Taherkhani & Pierre, 2012). The objective of congestion control in VANETs is to limit the data loads on the wireless network so that it can provide better access to the wireless platform through algorithms which reduce the transmission power of the nodes. There are several congestion control algorithms that has been proposed in VANETs to reduce network congestion. Vehicular cloud computing proposed by Talib et al. (2017), has been investigated as an architectural approach to aggregate resources and support congestion mitigation and services at scale. Other studies propose rate-control strategies. For instance, the multiplicative rate-decreasing algorithm was mentioned by Sepulcre (2011), reduces packet generation rate when channel load increases to prevent broadcast storms. Metaheuristic methods such as Tabu Search and multi-objective Tabu variants have been applied by Taherkhani (2015) for scheduling and multi-objective congestion control (minimizing delay, jitter and loss). Power-control approaches, notably D-FPAV (Distributed Fair Power Adjustment) was discussed by Jackson and Vijayakumar (2018), adapt transmit power to keep beaconing load below a threshold and improve fairness of the network. Finally, Sepulcre (2011) also introduced beaconing strategies and hybrid methods that jointly adapt beacon rate, transmission power and MAC contention parameters have been surveyed and shown effective in reducing channel congestion while maintaining awareness.

Despite their promising performance in past studies, the proposed algorithms still face notable shortcomings. The first issue raised is the incompetent utilization of the connection capacity if the connection is shared by multiple sources and dropout of data packets if congestion happens. Secondly, the proposed algorithms could not prevent congestion over the network where it cannot avoid fluctuations in the transmission power or packet generation adjustment process. Third, the efficiency issue in the communication between equipment and security aspects in the network. Fourth, the limitation in determining which network in the connection is no longer saturated and status of power value of vehicles connected in the network.

In order to enable smooth communication and information interchange between V2V and V2I, VANETs has been improvised through merging with Internet of Things (IoT). Nowadays, IoT has been increasingly a growing topic in the area of road safety which produces great impacts on society and their life. IoT network connects millions of components, from human to small non-living things. With the support of IoT, the efficiency of the network can be increased which leads to a better and improved ITS (Elias et al., 2019).

## 2.4 The Internet of Things (IoT)

With the advent of smart homes, smart cities, and smart everything, IoT has emerged as an area of incredible impact, potential, and growth, with Cisco Inc. predicting to have 40 billion connected devices by 2030 (Sinha, 2024). It continues to confirm its important position in the context of Information and Communication

Technologies by opening tremendous opportunities for many novel applications that promise to improve the quality of our lives. In recent years, IoT has gained much attention that creates excitement and anxiety around the world (Lia, Xu & Zhao, 2018; Aldowah et al., 2018). Figure 2.5 shows the global IoT market forecast towards the year of 2030 (Sinha, 2024).

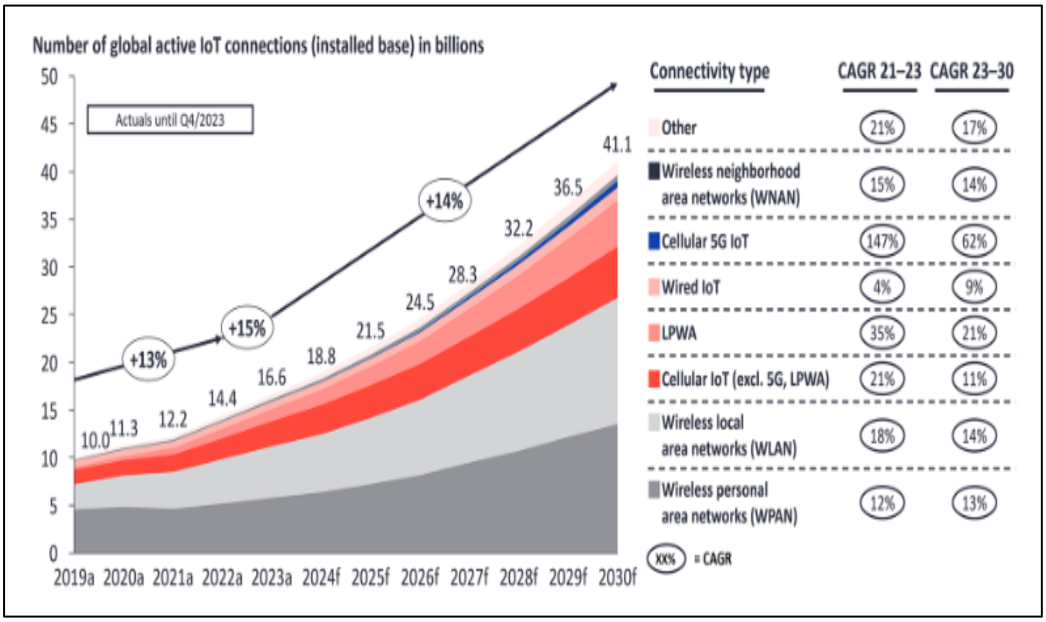



Figure 2.5 The Statistics of Market Forecast

IoT refers to the networked interconnection of everyday objects, which are often equipped with ubiquitous intelligence. IoT will increase the ubiquity of the Internet by integrating every object for interaction via embedded systems, which leads to a highly distributed network of devices communicating with human beings as well as other devices (Aldowah et al., 2018). The opportunity of interacting with lots of everyday objects connected to the Internet allows individual to access unlimited information anytime and anywhere. This vision opens a new horizon of ideas and developments that is already being considered by research scholars and academics. The context of IoT is illustrated in Figure 2.6 and Figure 2.7.

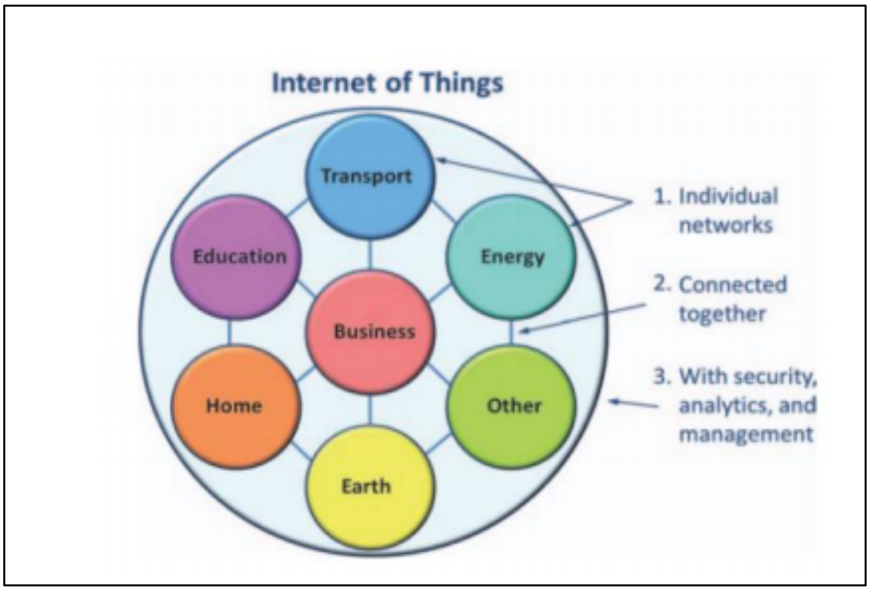



Figure 2.6 IoT Viewed as a Global Network (Cisco IBSG, April 2011)

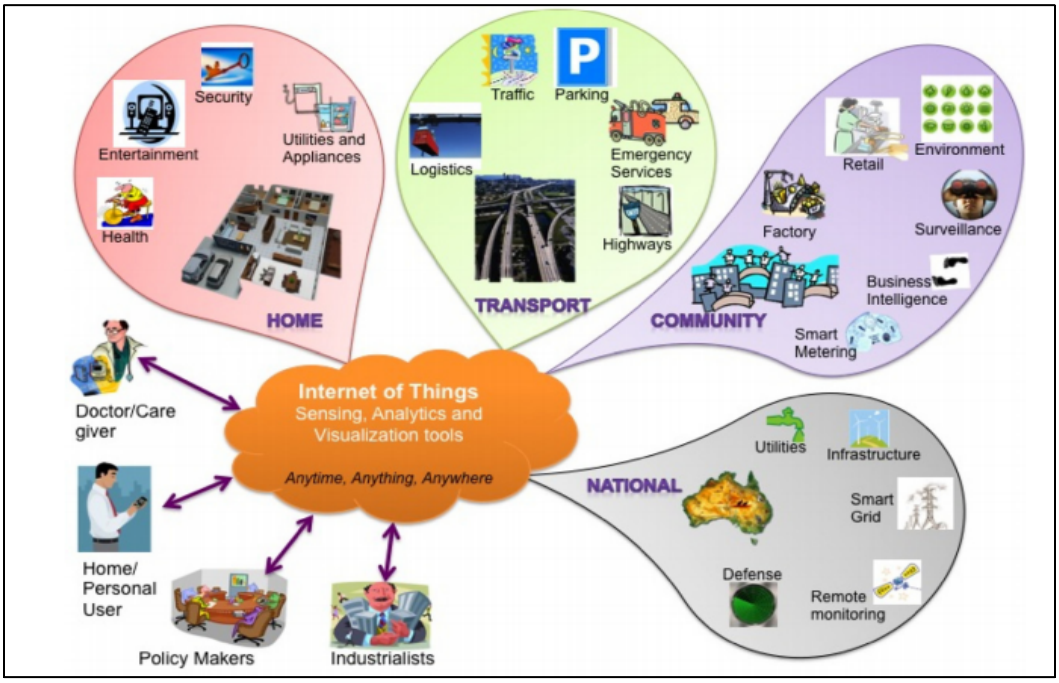



Figure 2.7 IoT Schematic Showing the End Users and Application Areas (Mansor, 2017; Gubbi, Buyya, Marusic & Palaniswami, 2013)

IoT can be realized in three paradigms which are internet-oriented (middleware), things oriented (sensors) and semantic-oriented (knowledge). Although this type of explanation is required due to the interdisciplinary nature of the subject, the usefulness of IoT can be unleashed only in an application domain where the three paradigms intersect. IoT also can be defined as the worldwide network of interconnected objects uniquely addressable based on standard communication protocols (Sari et al., 2017; Mansor, 2017). ‘Things’ are defined as the active participants in business, information and social processes where they are enabled to interact and communicate among themselves and with the environment by exchanging data and information sensed about the environment, while reacting autonomously to the real/physical world events and influencing it by running processes that trigger actions and create services with or without direct human intervention. Meanwhile, a smart environment uses information and communications technologies to make the critical infrastructure components and services of administration of a city, education, healthcare, public safety, real estate, transportation and utilities more aware, interactive and efficient (Mansor, 2017; Gubbi et al., 2013).

As mentioned in sub-chapter 2.3.2, due to the weakness of the existing VANETs, researchers in the area turned into integrating VANETs with IoT as a method for congestion control to solve the problem of network congestion. They have tried to emerged networking paradigms such as Software Defined Networking (SDN); proposed for wired environment with fog computing (for real-time processing purpose) since fog is considered as a cloud server known as one of the components in IoT to provide attractive approach in existing VANETs (Truong, 2015). SDN can enable VANETs to alter the network topology changes (Talib et al., 2017). The proposed architecture by combining safety through data streaming and non-safety services through lane-change assistance, managed to reduce the latency of the VANETs.

VANETs also is proven to work for Smart Accident Management System where the authors combined IoT and VANETs to propose a new framework for automated accident alerting and traffic optimization (Chatrapathi et al., 2015). Surprisingly, the combination produces great result which allows the VANETs entities vehicles, ambulance and hospitals to sustain the network themselves. In this framework, ambulance can receive the information on the shortest path (using A* algorithm) to the accident zone and also obtain the information on the nearest nearby hospital through GPS and the cloud server whereas hospital can prepare for the suitable treatment before the patient reaches the hospital according to the patient’s condition signal sent by the ambulance (Chatrapathi et al., 2015). The system organization is illustrated in Figure 2.7.

IoT in VANETs has also been successfully applied in real-time decision making for IoT-based traffic light control using a game theoretical approach, whereby Hoai and

Camacho (2016) proposed a method to reduce congestion at intersections by prioritizing emergency vehicles such as ambulances, patrol cars, and fire engines. Similarly, Jain (2018) introduced a city lane and intersection model to manage vehicle mobility, showing improvements in both congestion control and road safety. These works demonstrate the potential of IoT-based systems in addressing localized congestion at intersections.

However, traffic congestion remains a broader and more persistent challenge that extends beyond intersections, with far-reaching consequences on safety, mobility and quality of life (Talib et al., 2017; Perova, 2016). The main cause of urban congestion often lies in the sheer increase of circulating vehicles within a limited road capacity (Talib et al., 2017; Contreras et al., 2017; Chao et al., 2017). Recent developments in Command, Control, Communications, Computers, and Intelligence (C4I) technologies have enabled the proliferation of intelligent devices equipped with wireless communication and embedded processors. These smart devices contribute to creating safer and more efficient environments by forming a new era of IoT applications (Talib et al., 2017; Contreras et al., 2017). Within this context, scalable congestion control mechanisms have been proposed to improve the dissemination of event-driven safety messages in VANETs. In dense networks, the dedicated control channel becomes easily congested by periodic safety messages and broadcast storms generated from event-driven transmissions (Darus & Bakar, 2011). Congestion control frameworks address this challenge by scanning message queues and monitoring channel usage based on predefined thresholds. Additionally, a priority-based EDF scheduling algorithm has been introduced to ensure reliable performance by scheduling packets with equal high priority for event-driven safety messages. Table 2.4 summarizes existing research on IoT-based VANETs.

Table 2.4
IoT-based VANETs Systems

| | **System** | **Main Idea** |
|---|---|---|
| 1 | Software Defined Networking-based Vehicular Adhoc Network with Fog Computing (Talib et al., 2017) | Emerged SDN with fog computing algorithm in VANET |
| 2 | VANET based Integrated Framework for Smart Accident Management System (Chatrapathi et al., 2015) | Integrated IoT and A* Algorithm into VANET |
| 3 | Game Theoretic Approach on Real-Time Decision Making for IoT based Traffic Light | Gaming with IoT in VANET |

| | | |
|---|---|---|
| | Control (Hoai and Camacho, 2016) | |
| 4 | A Congestion Control System based on VANET for Small Length Road (Chao et al., 2017) | The structure of BUS-VANET |
| 5 | Converging VANET with Vehicular Cloud Networks to Reduce the Traffic Congestions: A Review (Contreras et al., 2017) | Discussion on the possible components of VANET and IoT (Vehicular Cloud Computing) to solve traffic flow |
| 6 | Congestion Control Framework for Disseminating Safety Messages in Vehicular Adhoc Networks (VANETs) (Darus & Bakar, 2011) | Scalable congestion control method based on defined threshold and EDF scheduling algorithm |

Somehow in IoT, most end-users' trajectories follow a random walk model (RW) and IoT focuses on things and provides data-awareness for connected things, whereas the Internet concentrates on people and offers information services to people (Yang, 2014). Another highlight on the limitation of IoT-based VANETs is the high vulnerability to network congestion and network attacks (Khezri et al., 2025; Khana & Salah, 2017). Thus, IoT has made a great turn by switching the conventional IoT-based VANETs into Internet of Vehicles (IoV) which promises huge commercial attention to its recognition and research value. As a result, it had opened new windows of possibilities and applications in improving transportation and mobility (Kaiwartya et al., 2016; Yang et al., 2014; Ovidiu, Vermesan & Friess, 2013). In IoV network, an individual vehicle or is considered a "thing" that could 'speak' for itself. This revolution of innovative technology advancement has out bounded the scope on large applications.

## 2.5 The Internet of Vehicles (IoV)

IoV has become a key enabling technology to realize future autonomous driving scenarios. It is an open and integrated network system with high manageability, controllability, operationalization and credibility and is composed of multiples vehicles, things and network (Yang et al., 2014). It is known as the extension of IoT which means that all vehicles are connected to each other using the Internet (Hamid et al., 2019). It also can be seen as the superset of VANETs where it encompasses the technology of VANET in terms of scale, structure and applications (Cheng et al., 2015). Vehicles are allowed to share important data such as sensory data, risk data, environmental data and localization data among them.

IoV has been implemented as application in several domains, for instance smart home, smart energy, smart healthcare, smart environment, smart transportation and smart city. The integration of all participants communication in the IoV ecosystem which consists of humans, sensors and vehicles, becomes one of the challenges to be solved (Ang et al., 2019; Sharma & Mohan, 2017; Kaiwartya et al., 2016). Figure 2.8 shows the IoV applications in various areas, whereas Figure 2.9 shows the basic IoV network architecture.

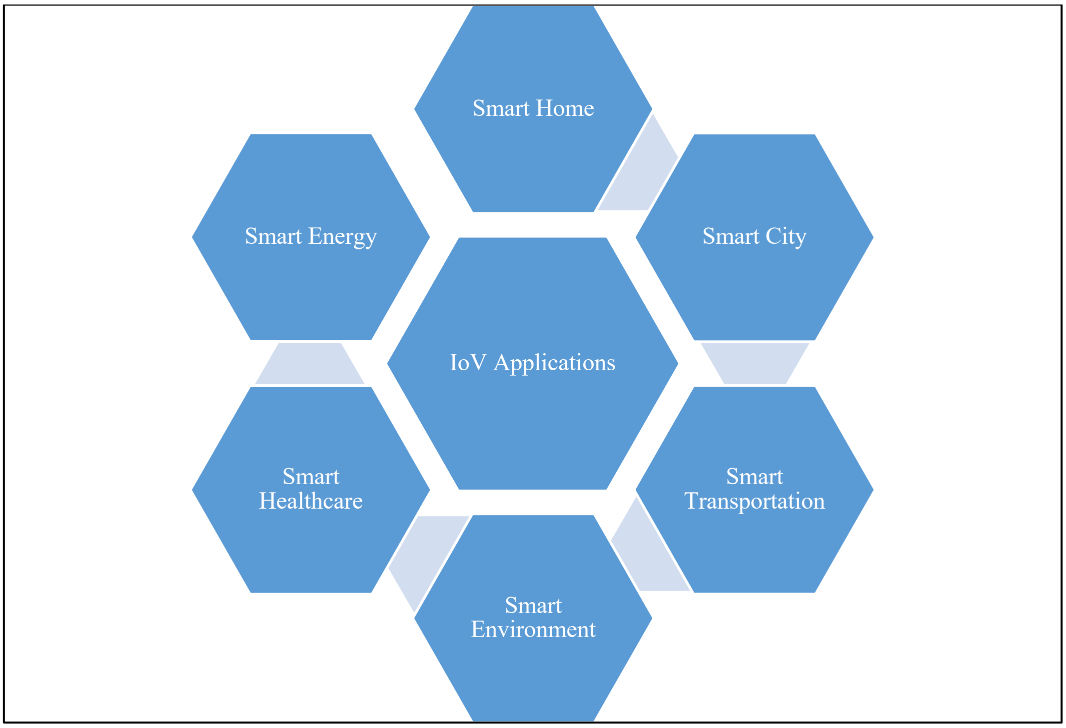



Figure 2.8 IoV Applications (Sharma & Mohan, 2017)

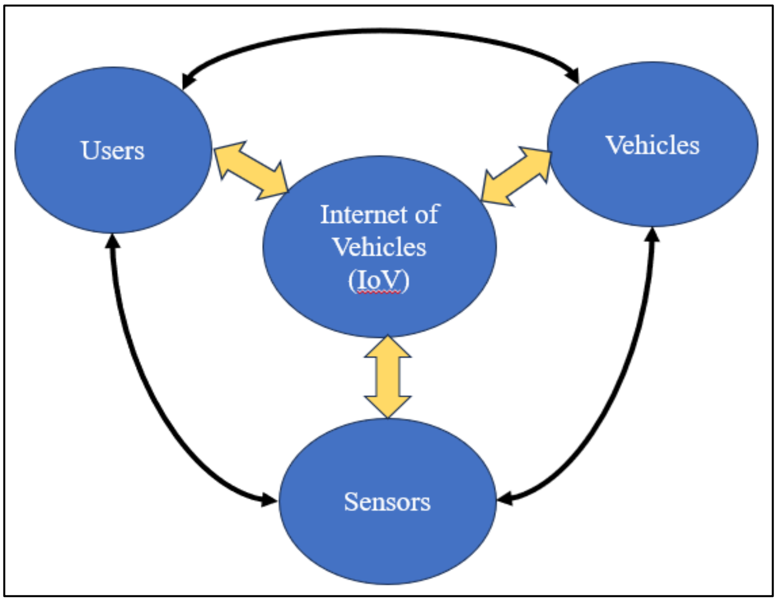



Figure 2.9 IoV Network Architecture (Hamid et al., 2019)

IoV network has equipped with several advantages such as high-speed mobility, delay sensitivity, uninterrupted network connection, robust and secure network. IoV consists of two main parts which are the networking and its intelligential (Khezri et al., 2025; Hamid et al., 2019). The combination of the two components will permit for the interconnection of vehicles, vehicle telematics and mobile Internet. Recently, the limited implementation of IoV network has been done, with most of the implementation only focusing on the enhancement of the user experience and to improve the active safety feature of the vehicle on collision avoidance system (Hamid et al., 2019).

Nevertheless, to guarantee smooth connectivity and data sharing between automobiles, infrastructure, and outside entities, a variety of communication methods are available in IoV network. IoV network accommodates ITS, which it offers the ability to provide vehicle-to-everything (V2X) interactions depends on these communication channels. The major types of communication channels in an IoV network includes vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-roadside Unit (V2R), vehicle-to-pedestrian (V2P), vehicle-to-cloud (V2C) and in some perspective vehicle-to-personal devices (V2P), vehicle-to-sensor (V2S) (Talib et al., 2017; Kaiwartya et al., 2016; Lu et al., 2014). This communication is extremely important to be established in an ITS architecture especially to improve traffic flow, reducing congestion and minimizing frequent road accidents (Sharma & Mohan, 2017; Gozalvez et al., 2012).

While safety and non-safety applications were found in VANETs through localized V2V and V2I communication, IoV network expands this functionality by integrating vehicles with IoT, cloud computing and big data analytics. Within the IoV framework, V2V benefits from integration with cloud services, edge computing and AI-driven analytics, enabling vehicles to share not just position and speed but also contextual information such as sensor data, intent prediction, and road condition assessments. As a result, vehicles can collectively respond to dynamic road situations. Safety applications are among the most critical components of the IoV network. It is designed to enhance road safety, reduce traffic accidents and protect the lives of drivers, passengers and pedestrians. Figure 2.10 shows the diversity in V2X Communication for various applications.

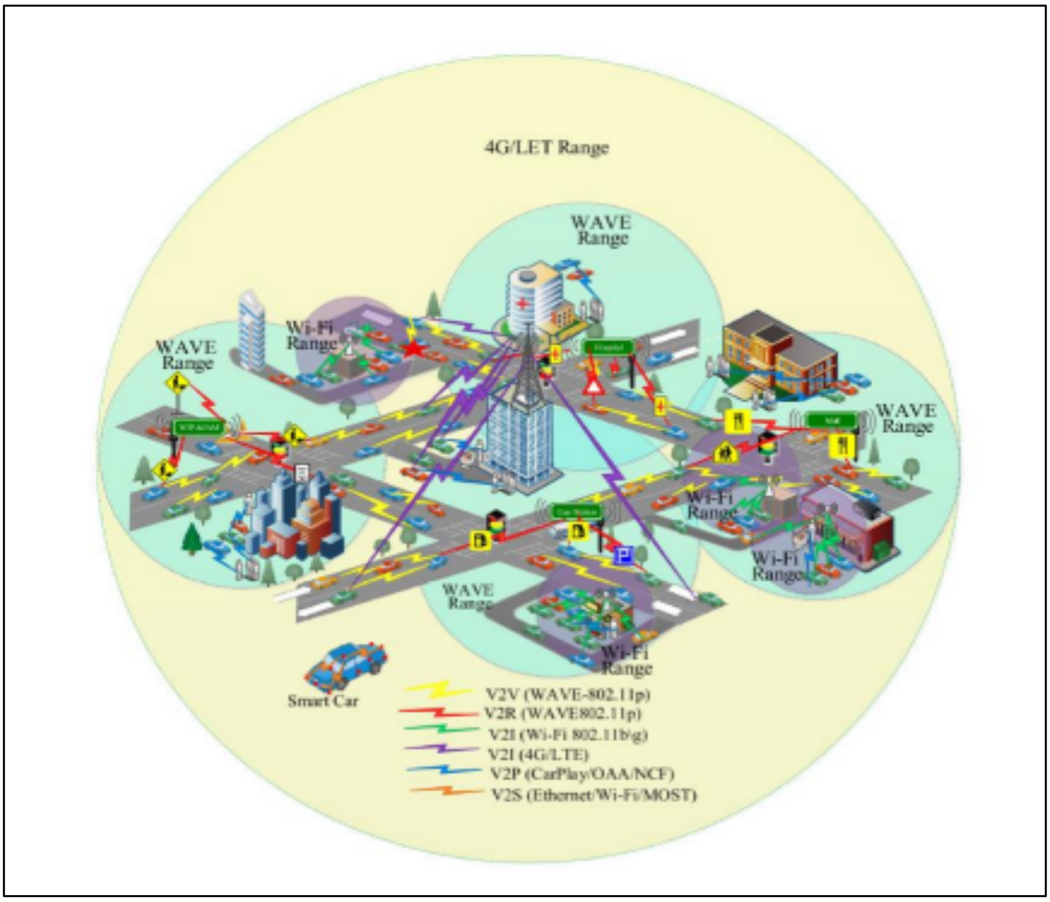



Figure 2.10 A Diversity of V2X Connection in IoV Network (Kaiwartya et al., 2016)

The illustration in Figure 2.10 demonstrates how diverse V2X communication technologies collectively contribute to an intelligent and interconnected transportation ecosystem. While such advancements have significantly enhanced vehicular communication capabilities, they also mark a transition from traditional VANETs toward more comprehensive IoV frameworks. As mentioned in sub-chapter 2.4, VANETs are facing declining adoption due to limitations in topology management and connectivity (Khezri et al., 2025). In contrast to VANETs, the IoV network aims to improve traffic efficiency and safety while integrating multiple communication media and enabling commercial infotainment services.

The availability of periodic messages in IoV network drives up demand since it gives passengers access to important online service such as remote access monitoring. The experience of travellers on the road is showing positive improvement (Zamrai et al., 2021; Sharma & Kaushik, 2019; Contreras-Castillo et al., 2017). Table 2.5 summarizes the differences between VANETs and IoV network.

Table 2.5
The Differences of VANETs and IoV network

| Parameters | VANETs | IoV Network |
|---|---|---|
| Purpose | • To enhance traffic safety<br>• To avoid catastrophe casualties and improve traffics efficiency<br>• To minimize time, cost, and pollutant emission. | • To enhance traffic safety, efficiency, and commercial infotainment.<br>• The infotainment that available in IoV network increases the demands as it provides opportunities for the passengers to access online services, including online music, video streaming and remote access monitoring. |
| Principles of communication | • Vehicle-to-Vehicle (V2V)<br>• Vehicle-to-Infrastructure (V2I) | • vehicle-to-vehicle (V2V)<br>• vehicle-to-infrastructure(V2I)<br>• vehicle-to-sensors (V2S)<br>• vehicle-to-everything (V2X) |
| Communication technology | Two types of communication technology:<br>• Wireless Access in Vehicular Environment (WAVE):<br>i. Dedicated Short Range Communication (DSRC)<br>• Continuous Air Interface for Long and Medium range (CALM)<br>i. GSM2G/GPRS-2.5G<br>ii. UMTS-3G<br>iii. Infrared communication | Five types of communication technology:<br>• Wireless Access in Vehicular Environment (WAVE):<br>i. Dedicated Short Range Communication (DSRC)<br>• Continuous Air Interface for Long and Medium range (CALM)<br>i. GSM2G/GPRS-2.5G<br>ii. UMTS-3G<br>iii. Infrared communication<br>• Bluetooth<br>• ZigBee<br>• 4G/5G/LTE |
| Compatibility | Compatibility problems arise because the personal device cannot communicate with the vehicle due to the underlying incompatible network architecture. | The integration of information flow among various nodes, such as smart and personal gadgets, is made possible by the built-in IoT capabilities. |
| Usability | Localized and discrete, it is appropriate for small-scale applications such as warning drivers of accidents on the roadways or preventing collisions. | Possess the ability to be flexible and sustainable, as well as communication and computing networks. |
| Power of Processing | Limitation on the amount of computing and processing power available to manage the local data collected by the sensors around the environment. | Due to the connection of the networks to the cloud, cloud computing is used for big data analytics. The processing, which involves real-time data collecting and analysis, is done on the cloud. |

As summarized in Table 2.5, the IoV network enhances the traditional VANET framework through the integration of heterogeneous communication technologies, broader connectivity and increased service diversity. These advancements are driven through intelligent in-vehicle systems that act as the central communication and processing components within the IoV architecture. In this context, the intelligent embedded vehicle-carried OBU system serves as a vital element of the IoV network.

Equipped with advanced wireless technologies such as IoT, DSRC, long-term evolution/fourth generation (LTE/4G) mobile communications, GPS/BDS navigation and positioning systems and mobile broadband, vehicles fitted with intelligent embedded OBUs continuously collect, process and transmit data regarding their position, speed and surrounding road conditions. These OBUs enable seamless information exchange between vehicles and infrastructure, ensuring real-time awareness, cooperative decision-making and efficient traffic management within the IoV environment (Hu, Wang & Zhao, 2020). The following section introduces the IoV network model, which outlines the structural components, communication layers and data exchange processes that support the interaction between vehicles, infrastructure, and cloud systems within this intelligent ecosystem.

### 2.5.1 IoV Network Model

IoV network was introduced based on layered design. The initial IoV network model was introduced by Nanjie (2011) in three-layered structures; the client, the connection and the cloud. The client layer is responsible for capturing all the information concerning the events that occur in the vehicle. This includes driving patterns as well as intra and inter-vehicular connections with other vehicles. The sensors of the vehicle are reliable for vehicle speed, position, tire pressure, oil pressure, proximity, pollution levels, noise, collision detection, forward obstacle, side obstacle, road-to-vehicle and road condition in this layer. On the other hand, connection layer is responsible for the interoperability with all the available networks to assist in all the V2X communication. Information is sent to the cloud layer which offers three sublayers of the cloud which are cloud infrastructure, cloud services and cloud applications. This layer will provide the necessary computational power required to comply with all the requirements of the vehicles for instance the sharing of communication medium, storage of data, exploration and analysis of information since IoV is an environment of cloud-based vehicle operation information platform.

Another three-layered architecture was introduced by Wan et al. (2014) which contains of vehicular, location and cloud layers. The vehicular layer responsible for managing all the internal sensors in the vehicles as well as responsible for obtaining ambient and physiological parameters information such as blood pressure, heart rate, mood behaviour of  driver and passengers of the vehicle. This is done through the shortrange wireless technology. This architecture enables information interchange with the neighbouring cars. If the vehicle is out of range, the information interchange is attained by using multi-hop communications with the support from roadside communication units (RSUs). Meanwhile, cloud layer provides access to historical traffic information to road users.

On the other hand, a four-layered architecture was also introduced by Bonomi (2013). The first layer contains vehicles, communication software for V2V and communication connections using the standard IEEE 802.11p protocol. The second layer; infrastructure allows connection among all the members in the IoV network in which the vehicle is located at any given time. The third layer which is the operation layer responsible for verifying and ensures the synchronization of the information management and flow. Nevertheless, the fourth layer which is the cloud layer signifies the type of cloud whether public, private or business, to receive data and information.

Next, a five-layered architecture was proposed by (Kaiwartya et al., 2016) which includes perception layer, coordination layer, Artificial Intelligence (AI) layer, application layer and business layer. Different types of sensors and actuators are represented in the perception layer. They are responsible to collect information from the various elements of other vehicles, RSUs and all connected devices (gadgets). On the other hand, the second layer which is the coordination layer utilizes a universal coordination module for network communications and manage the transfer of information that needs to be processed in the cloud system. As mentioned earlier, cloud system is responsible for storing, processing and analysing important information derived from the previous layers, whereas in business layer, statistical analysis was applied to come up with strategies through data visualization so a business model can be developed.

Later, authors (Contreras-Castillo et al., 2017) proposed a seven-layered network model which includes user interaction layer, data acquisition layer, data filtering and pre-processing layer, communication layer, control and management layer, business layer and security layer. The drivers of the vehicles can have a direct interaction through interface so they can be alerted with the current traffic flow or condition while they are travelling. For data acquisition layer, relevant data such as traffic information is gathered through all the sensors and devices in the network to ensure safety messages can be issued to the road drivers. Next is data filtering and pre-processing layer, whereby the gathered information can be analysed and some filtering on the data can be performed. It is very crucial to be carried out since it prevents irrelevant information from being disseminated as well as lowering the risk of the network traffic congestion.

The superlative network is then being selected in the communication layer with the purpose to send the information based on a number of selection parameters for instance, congestion and QoS level. This layer is the most prominent among the available layers for managing the various network service providers available within the IoV environment. This layer manages the data exchange among the different services including traffic management, traffic engineering and packet inspection. In addition, various types of cloud computing infrastructures are used to process significant amounts of information. Quite similar to the function of other architecture of the layer of the cloud, (storing, processing and analysing all the information received from the other layers) decisions are made based on statistical analysis and identifying strategies that help in applying business models. For this seven-layered architecture, another additional proposed layer is the security layer. It is critical and must be considered at all levels. All security functions such as data authentication, integrity, non-repudiation and confidentiality, access control, availability, among others are implemented. This is to ensures data exchange data among sensors, actuators, user’s devices will go through a secure networks and service providers. This layer is also designed to prevent various types of security attacks for example cyberattacks in IoV. The seven-layered architecture is illustrated in Figure 2.11.

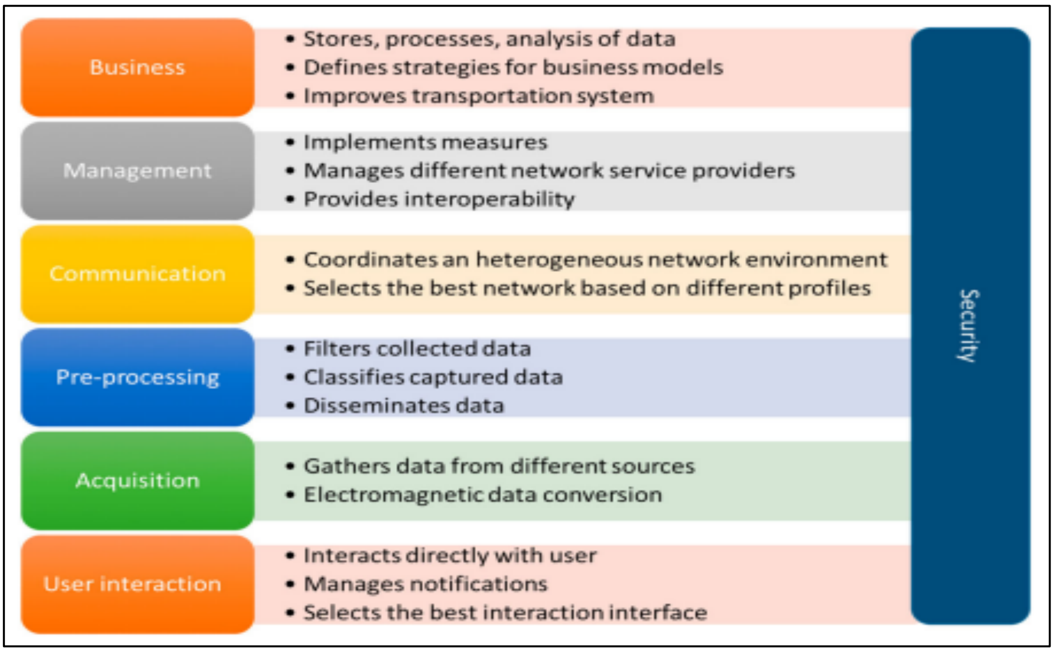



Figure 2.11 Seven-layered Architecture (Contreras-Castillo et al., 2017)

Figure 2.11 illustrates the seven-layer architecture of the IoV network, which has been elaborated in the preceding discussion. A clearer understanding of the evolution and diversity of IoV architectures can be achieved by examining their layered structures side by side. Table 2.6 presents a comparative summary of the models discussed, including both the foundational three-layered design and the more advanced seven-layered framework. This tabular overview highlights the functional scope, roles, and contributions of each layer, offering a concise reference for analysing how different architectural approaches address the complexities of vehicular communication, data processing, and system integration.

Table 2.6
Past Studies on IoV Architectures

| **Proposed architecture** | **Number of layers** | **Types of Layers** |
|---|---|---|
| (Nanjie, 2011) | Three-layered | Client, connection and cloud |
| (Wan et al., 2014) | Three-layered | Vehicle, location and cloud |
| (Bonomi, 2013) | Four-layered | Services, infrastructure operation and cloud |
| (Kaiwartya et al., 2016) | Five-layered | Perception, coordination, AI, application and business |
| (Contreras-Castillo et al., 2017) | Seven-layered | User interaction, data acquisition, data filtering and pre-processing, communication, control and management, business and security |

In addition to proposing a comprehensive seven-layered architecture for the IoV network in Figure 2.11, Contreras-Castillo et al. (2017) also introduced a set of standards to guide the development and deployment of IoV networks. These standards aim to ensure interoperability, scalability, and security across diverse vehicular communication systems. By formalizing the roles and interactions of each layer, ranging from user interaction and data acquisition to communication, control, business logic, and security. The authors provide a structured framework that supports consistent data exchange and reliable system performance. The inclusion of these standards is critical for harmonizing the integration of heterogeneous devices and technologies within the IoV ecosystem, thereby enabling more efficient and safer transportation environments. Figure 2.12 shows the standards for IoV network.

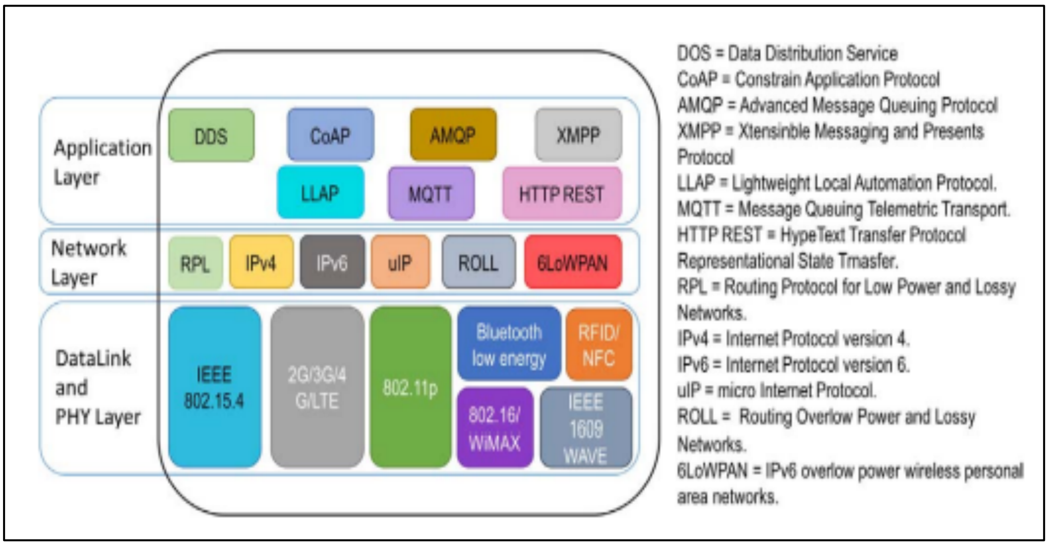



Figure 2.12 The Standards of IoV Network (Contreras-Castillo et al., 2017)

Figure 2.12 presents the standards that define communication in the IoV network, illustrating the protocols and technologies that enable interoperability and seamless data exchange among heterogeneous components. Moving towards the communication standards in IoV network, the communication standards of both IoV and VANETs vehicular networks are quite similar since IoV is a recognized as a superset of VANETs. It is based on the IEEE1609 Family of Standards for Wireless Access in Vehicular Environments (WAVE) which dependent on IEEE802.11p for Information Technology, telecommunications and information exchange among systems. The specifications defined by IEEE802.11p and IEEE1609 represent the most established set of standards for wireless vehicular networks at the physical layer (Hu et al., 2020; Elias, 2017; Kaiwartya et al., 2016).

In the network access layer, DSRC is one the most used wireless communication technology which is specifically designed for V2X communication. DSRC is based on IEEE802.11p standard and it enables vehicles to talk to each other. The structure of DSRC is divided into seven channels (CH) of 10 to 20 MHz each. In order to ensure efficient use of the spectrum, these channels are employed for various kinds of communication. The multi-channel architecture enables DSRC to prioritize safety-critical messages without neglecting less urgent or non-safety applications (Zhang et al., 2018; Elias, 2017). One channel is identified as a Control Channel (CCH) and another six channels are identified as Service Channels (SCHs). CCH is responsible for safety messages, whereas SCHs are responsible for non-safety applications (Mishra et al., 2023; Elias, 2017). Figure 2.13 below illustrates the seven channels of DSRC.

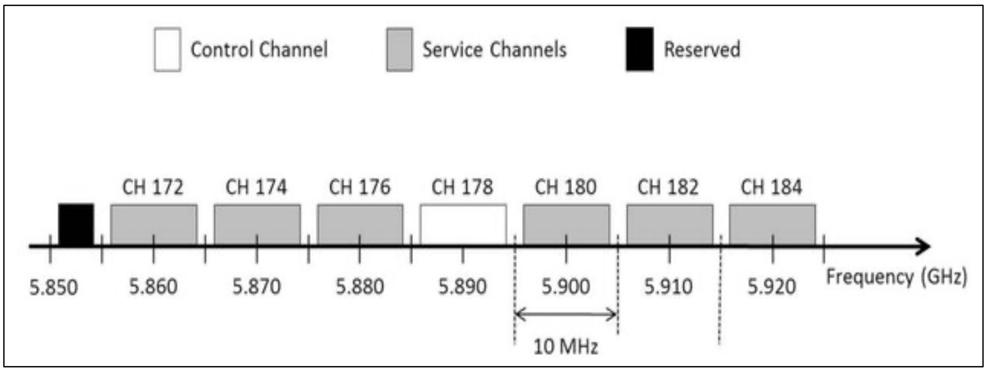



Figure 2.13 The Seven Channels of DSRC (Costandoiu & Leba, 2019)

In Figure 2.13, the CCH is also known as Channel 178. It is reserved for safety-based applications. Cooperative awareness messages or called beacon messages, are used by safety applications and are derived from periodic message exchanges of single-hop broadcast packets on CCH (Zhang et al., 2018). However, if there is less effort on how to improve the DSRC performance in the IoV network, it will definitely will seriously degrade the performance such as the throughput, PDR and packet delay in high vehicle load scenarios (Cao et al., 2021).

As IoV network is utilized to monitor the flow of vehicles, parking facilities and many other things produce enormous amounts of data, however the data provided by vehicles cannot be ignored by the smart city network in conjunction with the IoV network since it provides extremely sensitive information that helps to reduce traffic congestion (Mishra et al., 2022). When more data or control packets being injected into an intermediate node than the forwarding packets by the node within a certain period of time, congestion will occur. Thus, we have to ensure that CCH must be clear from any queuing packets or dense network in order to avoid the congestion. Nevertheless, poor performance can also be obtained when the transmission delay of a connection is high as most of the time the entire network would be transmitting only one packet. This situation leads to the under-utilization of the bandwidth of the network, which need to be avoided (Mishra et al., 2023). In other words, it is extremely crucial to have a balanced network connection for the communication of the nodes. Furthermore, the mobility models play an important role in order to execute the IoV network. It will be further discussed in the next sub-section.

#### *2.5.1.1 Mobility Models in IoV Network*

The IoV mobility model describes how vehicles communicate and move within an ITS. This model integrates various technologies, including the Internet of Things (IoT), cloud computing, and mobile networks, to enable the communication of vehicles (V2V, V2I, V2P, V2S and V2X). In urban city, the environment is classified as lower speed with a high density of vehicles at certain times (Hadded et al., 2015). In V2V routing, vehicles communicate with one another directly. These protocols can effectively convey data by taking advantage of the mobility and proximity of vehicles. The objective of mobility models is to simulate the movement patterns of vehicles to test and improve the performance of IoV systems. Common mobility models in IoV include Random Waypoint Model (RWP), Random Direction Mobility Model (RD), Random Walk Mobility Model (RW), Manhattan Mobility Model and Gauss-Markov Mobility Model (GMM).

a) Random Waypoint Mobility Model (RWP)

RWP is described as a discrete-time stochastic process where vehicles choose random destinations and travel to them at random speeds. Once they reach the destination, they wait for a random period before choosing the next destination. The RWP allows for flexibility where it offers incorporation of occasional pause times in modelling the mobility of users (Alenazi et al., 2020; Soltani et al., 2020). The Non-

Homogeneous Poisson Process (NHPP) is a statistical model usually used in RWP which describe events that occur randomly over time. It can be applied to model various dynamic and time-dependent aspects, such as vehicle arrivals, traffic patterns, and communication requests (Raja et al., 2020). Figure 2.14 below shows the RWP mobility.

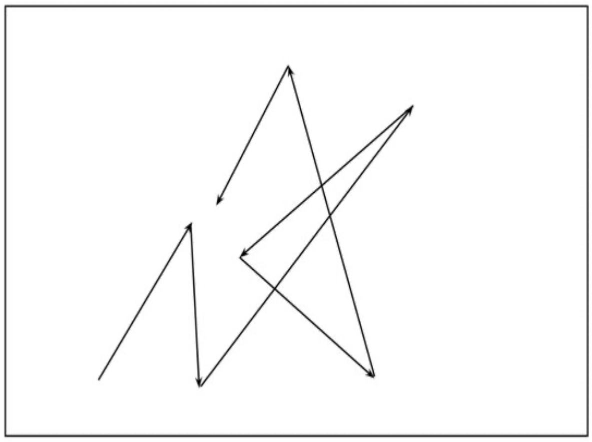


Figure 2.14 RWP mobility (Krishnaperumal & Thilak, 2023)

b) Random Direction Mobility Model (RD)

Since mobile users in both models travel in piece-wise linear chunks, the random direction (RD) mobility model and the random waypoint approach are nearly identical. They vary from one another, though, in how a user is dealt with once it crosses a border and how the next path is chosen. A mobile terminal updates its speed and direction values and reflects toward the simulation zone as soon as it approaches the border of the predefined area. In the random direction approach, the distributions for both speed and direction are simpler yet easier to execute. However, it is less physically appealing (Sakthivel & Balaram, 2021; Alenazi et al., 2020). Figure 2.15 below shows the RD mobility.

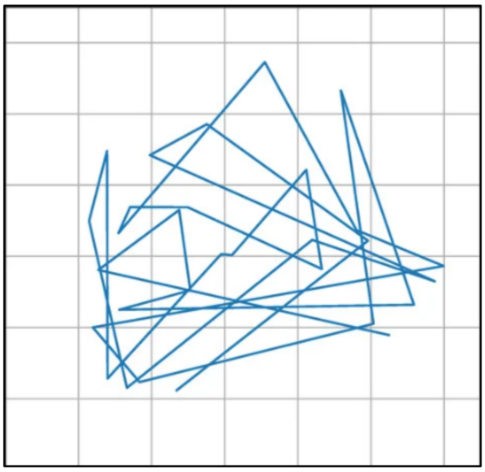


Figure 2.15 RD Mobility (Alenazi et al., 2020)

c) Random Walk Mobility Model (RW)

In contrast to the RWP model, the RW mobility strategy attempts to replicate human movements in urban streets and sidewalks, where users often take parallel, close steps in either the east-west or north-south directions. In comparison to previous random mobility models, the RW mobility model more closely resembles these traits and offers more realistic movement instances. The RW technique involves mobile nodes moving from their current places to the next step by choosing a random direction from the interval $[0,2\pi]$ and a random speed within a pre-defined range [min, max], however every step happens within a specified duration (t) or fixed distance (d). The procedure of selecting the next direction and speed is repeated in the same manner until the simulation process is ended (Alenazi, 2020). Figure 2.16 below shows the mobility of RW.

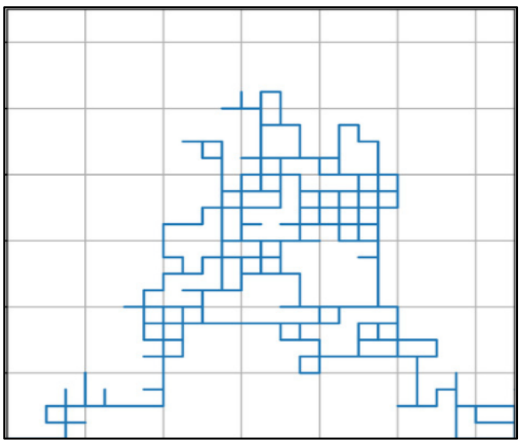


Figure 2.16 RW Mobility Model (Alenazi et al., 2020)

d) Manhattan Mobility Model

In Manhattan Mobility Model, vehicles move in a grid pattern, resembling urban environments. This model is only suitable for city scenarios where roads are laid out in a grid-like structure. Moreover, this model facilitates intersection behavior analysis (Alenazi et al., 2020; Hameed Mir & Felali, 2014). However, this model does not consider for real-world map irregularities unlike RWP. The example of the model is shown in Figure 2.17.

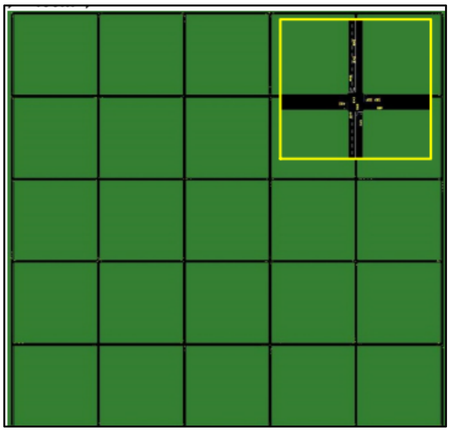


Figure 2.17 Manhattan Mobility Model (Hameed Mir & Felali, 2014)

e) Gauss-Markov Mobility Model (GMM)

Gauss-Markov Mobility Model (GMM) introduces randomness in direction and speed, influenced by previous velocity, making it suitable for suburban or less structured road networks. GMM takes advantage of temporal dependency to improve upon earlier methods. A mobile terminal updates its direction and speed based on previous data recorded at previous intervals. Furthermore, a degree of randomness is added to the calculation of these two numbers, which can be adjusted according to the characteristics of the simulated wireless network. Since the memories of earlier steps are retained, the GM mobility model is not stateless (Alenazi et al., 2020). This type of mobility model is suitable for airborne network such as Flying Adhoc Network (FANET) (Maakar et al., 2019). Mobile nodes are allocated in random locations within the wireless network. These nodes will set their speed and direction for each specific time interval. The example of GMM mobility is illustrated in Figure 2.18.

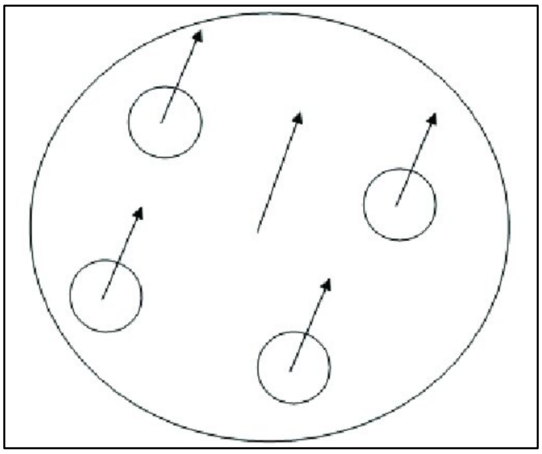


Figure 2.18 Gauss-Markov Mobility Model (Maakar et al., 2019)

Based on the comparison of the mobility models discussed above, this study adopts the RWP model integrated with a NHPP for vehicular movement simulation. The selection is primarily motivated by the need to evaluate congestion control and delay performance under dynamic, time-varying and density-fluctuating IoV environments, which closely resemble real-world vehicular communication scenarios.

The RWP mobility model offers a high degree of flexibility by allowing vehicles to move toward randomly selected destinations at variable speeds, interspersed with pause times. This behaviour effectively captures the stop-and-go nature of vehicular movement, particularly in urban and semi-urban traffic conditions where vehicles frequently decelerate, stop, and resume movement due to traffic signals, congestion, or road interactions. Unlike grid-based models such as Manhattan, RWP does not impose strict road constraints, enabling the study to focus on communication dynamics and congestion behaviour rather than road geometry.

To further enhance realism, the RWP model with the NHPP allows vehicle arrivals and communication events to vary over time. NHPP is well-suited for modelling time-dependent traffic intensity, such as peak and off-peak traffic periods, sudden increases in vehicle density, and transient congestion events. This is particularly important for IoV studies, where network load and channel utilization fluctuate significantly due to changing traffic conditions. By incorporating NHPP, the simulation is able to reflect non-uniform vehicle arrival patterns, which directly influence channel load, delay and packet collision probability.

Compared to other mobility models, RD and RW introduce movement behaviors that are less representative of vehicular traffic, such as frequent border reflections or step-wise direction changes that resemble pedestrian movement rather than vehicles. Although the Manhattan model is suitable for grid-based urban layouts, it limits the generality of the study and does not account for irregular road structures. Similarly, the Gauss-Markov Mobility Model introduces temporal dependency but is more commonly applied to airborne or less constrained networks, making it less suitable for evaluating dense terrestrial vehicular communication scenarios. Therefore, the combination of RWP with NHPP provides a balanced trade-off between model simplicity, realism and analytical flexibility.

Following the discussion on vehicular mobility models, it is important to note that the effectiveness of a mobility model is closely tied to the capabilities of the network simulator used to implement it. A suitable simulator must not only support the selected mobility model but also accurately represent wireless communication behaviour, protocol interactions and network dynamics under varying traffic conditions. Therefore, the choice of network simulator plays a critical role in ensuring that the mobility behaviour and communication performance are realistically captured in IoV simulation studies.

Understanding the interplay between mobility models and network simulators is essential for selecting appropriate tools in IoV network simulation studies. The comparative overview in Table 2.7 highlights the diversity of supported models and functional capabilities across popular simulators, offering valuable insights for researchers aiming to replicate realistic vehicular environments.

Table 2.7
Network Simulators (Singh, 2017)

| Simulator | Mobility Model | Opportunities |
|---|---|---|
| NS2 | Random Waypoint, Random Walk, Random Direction, Manhattan Grid and Gauss-Markov model | Visualization is an available and very popular simulator. |
| NS3 | Random Waypoint, Random Walk, Random Direction, Manhattan Grid and Gauss-Markov model | It supports TCP, UDP, ICMP, IPv4, multicast routing protocols, and CSMA protocols. |
| OPNET | Random Waypoint, Random Walk, Random Direction | It supports very large-scale multihop wireless networks. |
| OMNeT++ | Random Waypoint | Supports a graphical network editor and multihop wireless networks. |

| | | |
|---|---|---|
| GloMoSim | Random Waypoint, Random Walk, Manhattan Grid, Gauss-Markov model | It can scale up to networks with thousands of heterogeneous nodes. |
| NetSim | Random Waypoint, Random Walk | It provides a Graphical User Interface (GUI) with the features of drag and drops functionality for devices. |

Selecting an appropriate network simulator is critical for accurately modeling IoV environments, where vehicle mobility, communication protocols, and realistic traffic scenarios must be captured effectively. Table 2.7 compares popular simulators, highlighting their supported mobility models and functional capabilities. While NS3 and GloMoSim offer extensive protocol support and high scalability, they lack native vehicular mobility frameworks, which complicates the integration of realistic V2V communication scenarios. OMNeT++, in contrast, combines a flexible modular architecture with robust graphical visualization tools and seamless integration with vehicular frameworks such as Veins. These features enable rapid prototyping, detailed modeling of V2V interactions and incorporation of realistic traffic patterns, which are essential for the objectives of this research. Consequently, despite some simulators demonstrating advantages in raw protocol support or scalability, OMNeT++ was selected for this study as it offers the optimal balance of usability, visualization, and framework compatibility for IoV simulation.

### 2.5.2 Data Management in IoV Network

Data management in IoV network serves as the foundation for enabling real-time communication and connected vehicle services. Vehicles as the mobile data generators, consistently producing extensive and diverse information, including traffic conditions, location coordinates, sensor readings and infotainment content. The procedures to manage and handle the relevant data to the interests of drivers include data gathering, data aggregation, data validation and data dissemination. Each of the procedures must be able to operate according to the constraints of a highly dynamic environment. It involve rapid vehicle movement, frequent changing network topologies and heterogeneous communication (Mansor, 2017; Ilarri et al., 2015; Kakkasageri & Manvi, 2014).

#### *2.5.2.1 Data Gathering*

The process of exchanging distinct data related to the driver's necessity is made possible through the IoV network through the V2X communication. Information regarding safety-based messages is gathered through various sources as listed in Table 2.6. The purpose of these messages is to provide options for users while they are on the road. For instance, data on the vehicle speed and location can be obtained from the vehicle itself and from the surrounded sensors installed at the RSUs.

Routing protocol-based information gathering typically collect geographical data near the destination and return it to the original inquirer. On the other hand, pull-based data gathering provides the demanded information based on request. To access certain crucial information, this strategy would necessitate sending a query message to other vehicles on the network. In addition, information could also be obtained from crowdsourcing means of mobile application such as Waze whereby users of the application contribute information through their mobile devices (Mansor, 2017).

Despite of the success of this technology being adopted to create applications to help users aware with the situation and alerts, many issues were raised particularly on the information management aspect. In a fast-changing topology and high-speed mobility, the most prominent issue is ad-hoc connectivity and data sharing in V2V communication. This is owing to the fact that with fast mobility, there is a very little window of time for connections to be established and data to be collected and disseminated due to location and topology changes (Mansor, 2017; Allani, Yeferny, Chbeir, & Ben, 2016; Brennand et al., 2016; Cárdenas-benítez, Aquino-santos, & Magaña-espinoza, 2016; Ilarri et al., 2015; Stojmenovic, 2014; Wang, Deng, & Guo, 2014).

#### *2.5.2.2 Data Aggregation*

Data aggregation is the process of combining numerous pieces of information that are all connected to the same event into a single piece of data. When vehicles are required to not only spread their own information but also convey information from one neighbour to another, packets carrying the same information will become devastating. The goal of data aggregation is to integrate, update, or eliminate duplicated, similar, irrelevant, or expired data. The goal of data aggregation is to reduce bandwidth and storage utilisation. Data aggregation can be categorized into four categories which are centralized aggregation, fully distributed aggregation, cluster-based aggregation and hierarchical based aggregation (Mun et al., 2023; Mansor, 2017; Kakkasageri & Manvi, 2014).

i) Centralized aggregation

In centralized aggregation, a single node which is referred to as the central aggregator is responsible for collecting and aggregating data from all other nodes in the network. While this approach simplifies the data fusion process by maintaining a global view, it introduces a critical bottleneck near the central node. As all communication flows toward this core point, it can lead to severe congestion, increased latency, and a higher risk of data loss in its vicinity. Moreover, this approach poses a single point of failure risk, making it less suitable for highly dynamic and large-scale vehicular networks.

ii) Fully distributed aggregation

The fully distributed aggregation strategy delegates the data processing responsibility to individual nodes. Each vehicle aggregates data locally and independently, without relying on a centralized authority. This method enhances resilience and fault tolerance, as there is no dependency on a single point. However, as the number of nodes increases, the volume of inter-node communication also grows significantly, resulting in high communication overhead,especially in dense urban traffic environments. This can degrade network performance if it is not managed with suitable protocols.

iii) Cluster-based aggregation

Cluster-based aggregation groups vehicles into clusters based on certain criteria such as geographic proximity, speed, or mobility patterns. Each cluster picks a Cluster Head (CH) using multi-metric algorithms that consider factors like node stability, residual energy, and communication capability. The CH is responsible for aggregating data from cluster members and forwarding it to higher layers or external networks. This strategy is particularly well-suited for vehicular networks due to its scalability, localized communication and reduced redundancy. By limiting data exchange within clusters, it significantly decreases communication overhead and improves efficiency in highly mobile environments.

iv) Hierarchical aggregation

Hierarchical aggregation organizes nodes into multiple levels or layers of clusters. The member nodes send data to the local CH within each cluster, which aggregates the data and passes it to a higher-level CH node in the hierarchy. This structure allows for efficient multi-hop communication and data compression at various levels, thereby reducing the load on any single node or link. Hierarchical aggregation is highly effective for large-scale vehicular networks, offering a balance between data accuracy and bandwidth utilization (Ucar, Ergen, & Ozkasap, 2015).

#### *2.5.2.3 Data Validation*

Data validation refers to the process of verifying the accuracy, reliability, and completeness of the information exchanged within the vehicular network. It ensures that the transmitted data meets predefined requirements and can be trusted by receiving entities. Reliable data validation is essential for maintaining the integrity of communications, particularly in safety-based applications where incorrect or interfered information could lead to serious consequences. Such consequences include false traffic alerts that may mislead drivers into taking unnecessary route or cause increased congestion, safety hazards resulting from incorrect warnings such as emergency braking or collision alerts, potentially leading to accidents and denial of service (DoS) attacks, where the network is flooded with invalid data, disrupting the delivery of valid safety messages. Furthermore, a lack of proper validation could allow for the propagation of misinformation, affect a large number of vehicles, and even violate user privacy through unauthorized tracking or data harvesting. Ultimately, such failures undermine user trust in the system and diminish the effectiveness of IoV applications (Karim et al., 2023; Mansor, 2017).

An important consideration within data validation is user privacy, which poses significant challenges in vehicular networks due to the frequent broadcasting of sensitive information such as location, speed, and identity. To address these challenges, two primary mechanisms are commonly used are authentication-based validation and threshold-based validation. Authentication-based validation verifies the identity of the sender to ensure that the data originates from a trusted source. On the other hand, threshold-based validation evaluates the consistency of information received from multiple sources to detect anomalies or misinformation (Madhukar et al., 2024; Sikarwar & Das, 2022).

While data validation is indeed a fundamental component in most IoV applications, particularly those related to security and trust management, it falls outside the main focus of this research. This study prioritizes network optimization and congestion control rather than privacy preservation. Therefore, although data validation mechanisms are acknowledged, they are not explored in detail within the scope of this work.

#### *2.5.2.4 Data Dissemination*

Data dissemination is described as the process by which information is broadcasted from one vehicle to others within its communication range. This information can include safety messages, traffic updates, road conditions, and other situational awareness data. The volume of data being disseminated is typically proportional to the density of traffic and the frequency of events occurring on the road (Bodhke, 2024; Mansor, 2017).

This behaviour is analogous to the update mechanisms seen in traditional IP networks using Transmission Control Protocol (TCP) and User Datagram Protocol (UDP), where routing protocols such as Routing Information Protocol (RIP) or Open Shortest Path First (OSPF) are used to maintain up-to-date routing tables. In RIP, updates are sent at regular intervals using a distance-vector approach, while OSPF uses a link-state strategy for faster and more accurate updates.

However, IoV network differ significantly. While TCP ensures reliable transmission with acknowledgment and error checking, it introduces overhead and latency, which may not be ideal for the fast-paced, real-time communication needs of vehicular environments. On the other hand, User Datagram Protocol (UDP) offers low-latency communication by transmitting data without waiting for acknowledgments, thus make it more suitable for time-critical safety applications in IoV network, despite its lack of guaranteed delivery (Bodhke, 2024).

Therefore, although parallels can be drawn with traditional network models, the unique characteristics of vehicular environments such as high mobility, frequent topology changes and the need for low latency, demand specialized data dissemination strategies that move beyond the scope of standard TCP/IP-based models. Table 2.8 illustrates the summary of information taxonomy in IoV network.

Table 2.8
Information Management Taxonomy in IoV Network (Bodhke, 2024; Mansor, 2017)

| **Mechanism** | **Method** | **Description** |
|---|---|---|
| Data gathering | Routing protocol based | Routing protocols is used to determine the best path for data to travel from source vehicle to the destination. It is usually applied in multi-hop networks where direct communication is always possible. |
| | Pull based | Data is collected based on request. A central controller or server invoke data from vehicles or nodes when needed, reducing unnecessary transmissions and saving bandwidth. |
| Data aggregation | Centralized | All data is transmitted to a central node or server for aggregation and processing. It is straightforward yet has the potential to cause congestion. |
| | Fully distributed | Each node locally processes and aggregates data prior to transmission. It enhances scalability and fault tolerance. |
| | Cluster based | The network is segmented into clusters, with each cluster have a cluster head. It is tasked with the collection and aggregation of data from the members of the cluster. Thus, it distributes load and mitigates congestion. |
| | Hierarchical based | A multi-level structure is used to aggregate data progressively through each layer. It is efficient for large-scale network. |
| Data validation | Authentication based | The identity of data sources is authenticated through digital signatures or certificates to prevent spoofing or malicious data injection. |
| | Threshold based | Data is validated based on predefined threshold or rules. |
| Data dissemination | Forwarding based | Data is forwarded hop-by-hop through intermediate nodes until it reaches the destination. It reduces network flooding. |
| | Broadcast based | Data is sent by the source vehicle to all nodes in |

| | | |
|---|---|---|
| | | range. It is effective for distributing emergency message such as collision alerts especially for real-time transmission. |
| | Push-based | Data is sent dynamically from the source to the destination (cloud server) without being requested. Similar to broadcast based, it is also suitable for real-time application such as for collision warnings. |
| | Routing protocols based | It is used to determine efficient dissemination route, especially in V2V or V2I communication. |

Table 2.8 provides a structured taxonomy of information management in IoV networks, categorizing mechanisms for data gathering, aggregation, validation, and dissemination. Its importance lies in highlighting critical challenges such as congestion, latency and data redundancy, which must be addressed to ensure efficient and reliable communication. In this study, the table informs the design of the proposed V2V communication model, supporting the use of distributed data aggregation and event-driven dissemination. By integrating these mechanisms with PSO-based optimization, the table underpins the reliability and real-time performance of the model for applications including collision avoidance, traffic flow optimization, and V2C services.

Despite the advancements outlined in Table 2.8, previous studies indicate that data dissemination in IoV networks is heavily impacted by several dynamic factors, including high vehicle mobility, frequent topology changes, large-scale and high-density node environments, low penetration ratios and elevated packet loss rates (Kapassa et al., 2021; Lone, Verma & Sharma, 2021; Sharma & Kaushik, 2019; Kumar & Dave, 2012). These factors collectively pose significant challenges to maintaining stable and reliable network performance, particularly in dense and rapidly changing vehicular environments. Understanding these limitations is essential for designing effective communication strategies that ensure timely and accurate information delivery.

The challenges highlighted here underscore the critical need for advanced mechanisms in congestion control, network connectivity, decision-making and security management. In the context of this study, they provide the rationale for adopting distributed aggregation, event-driven dissemination and PSO-based optimization approach in the proposed V2V communication model, enabling it to address the inherent instability and unreliability present in real-world IoV networks.

### 2.5.3 Challenges in Managing IoV Network

Although IoV networks offer substantial advantages over traditional VANETs, achieving a fully operational and efficient IoV ecosystem remains a complex task. The integration of heterogeneous technologies, high mobility of vehicles and dynamic network topologies introduce multiple management challenges. Among the most significant are congestion control, connectivity and scalability issues, as well as security and privacy concerns that continue to hinder stable communication and reliable data exchange (Kapassa et al., 2021; Lone, Verma & Sharma, 2021; Sharma & Kaushik, 2019). Table 2.9 summarizes these key challenges currently faced in the IoV network.

Table 2.9
Major Challenges in Managing IoV Network

| **Features** | **Challenges** |
|---|---|
| Congestion control | IoV network is established based on wireless communication network in which all the interactions of the components are done wirelessly thus, lead towards network complexity (Kapassa et al., 2021; Mahmood, 2020). It is expected to provide mission-critical message for the participants. However, the characteristics such as connectivity, bandwidth, vehicle mobility and data transfer speed can cause difficulty such as packets flooding in disseminating the safety-related messages. The situation will lead to data loss and packet delivery delay. QoS will strongly affected if congestion happened (Sadiq et al., 2021; Kapassa et al., 2021; Liu et al., 2019). |
| Network connectivity and scalability | The combination of various components of IoV network such as devices, protocols and platforms, may present new challenge in the interaction or connection between the components in terms of information consumption and sharing (interoperability) (Kapassa et al., 2021; Sherazi et al., 2019). It is difficult to accurately calculate the number of nodes in a network (Kapassa et al., 2021) as frequent network topology changes may occur due to high mobility of vehicles. The vehicles or nodes will face difficulties in maintaining a stable and real-time communication (Kapassa et al., 2021; Tripathi, Ahad & Sathiyanarayanan, 2019; Kim, 2019). |
| Decision making | Artificial Intelligence (AI) creates intelligent transportation which lead |

| | |
|---|---|
| | to intelligent decision-making. Unfortunately, there is a lacking in computing resources and the processing of untrustworthy data and difficulties in AI task allocation. This is due to the restriction on the availability of resources which leads towards the problem in the implementation (Kapassa et al., 2021; Hammoud, Sami, Mourad, Otrok, Mizouni & Bentahar, 2020). In addition, the management of the IoV network resources and traffic schedule also becomes a challenge to be carried out (Kapassa et al., 2021; Ning, Dong, Wang, Rodrigues & Xia, 2019). IoV network does suffers from the complication since many AI algorithms rely strongly on the vehicles data for the purpose of models training (Mollah, Zhao, Niyato, Guan, Yuen, Sun, Lam, & Koh, 2021). |
| Privacy and security | The components of the IoV network (for example, vehicles and RSUs) are prone to unauthorised access and illegal conduct, posing a security and reliability hazard. Malicious vehicles may initiate attacks such as denial of service (DoS) attack on other vehicles, causing instability and unreliability in the IoV system (Kapassa et al., 2021; Baza et al., 2021; Sakiz & Sen, 2017). In terms of the communication, there are substantial concerns about the creation of secure and rapid interactions across the IoV ecosystem (Jabbar, Fetais, Kharbeche, Krichen, Barkaoui, & Shinoy, 2019). Privacy is not guaranteed during resource-sharing process due to the unpredictable mobility and topology (Kapassa et al., 2021; Chai et al., 2019). |

Among the listed challenges in Table 2.9, congestion control stands out as the most critical because it has a direct and immediate impact on QoS in IoV network. Unlike connectivity and scalability, which affect the long-term adaptability of the system, congestion control directly influences the real-time delivery of safety-critical messages such as collision warnings and traffic alerts. If congestion occurs, the wireless channel becomes overloaded, leading to packet collisions, longer delays and even packet drops. This not only degrades throughput and PDR but can also cause mission-critical information to arrive too late, risking human lives. In contrast, issues such as connectivity, scalability or decision-making delays are important but often degrade performance gradually or can be mitigated with redundancy and adaptive protocols. Similarly, privacy and security are long-term trust and reliability concerns, but they do not instantly disrupt the delivery of urgent safety messages. Therefore, congestion control is prioritized because it is the bottleneck that most immediately threatens the reliability, timeliness and safety assurance of vehicular communication.

### 2.5.4 Congestion Control in IoV Network

Apparently, researchers in the area would rather concentrate on preventing congestion because it greatly reduces the throughput of the network and energy usage. There is a growing evidences to support the view. Four main strategies proposed to avoid network congestion are network scheduling, detection of congestion, notification of congestion and algorithm of congestion avoidance (Mishra et al., 2023; Zhang el al., 2018).

i) Network scheduling

In V2V communication, the network scheduling component within each vehicle node plays a vital role in ensuring reliable and timely data exchange. It is responsible for overseeing both the reception and transmission of packets between vehicles, managing how data is sent and received to support continuous and efficient communication. This component also handles the active packet queue by organizing packet sequences, applying packet drop strategies during congestion, and dynamically adjusting packet priorities based on the urgency and type of message such as giving precedence to safety alerts over non-critical data. Such adaptive queue management is essential in vehicular environments where network conditions can change rapidly due to high mobility and varying traffic density. By maintaining Quality of Service (QoS) and ensuring fairness across different data flows, the scheduler contributes significantly to the responsiveness, stability, and overall performance of the V2V communication system, which is critical for applications like collision avoidance, traffic coordination, and real-time navigation updates.

ii) Detection of congestion

Congestion detection is a crucial mechanism for maintaining efficient and reliable data communication among highly mobile and densely distributed nodes such as vehicles and roadside units in IoV network. Early detection of congestion allows the system to proactively manage network resources, minimize packet loss, reduce transmission delays, and ensure consistent QoS for critical applications such as traffic safety and real-time navigation. Various methods are employed to detect congestion in IoV environments. Round-trip time (RTT)-based detection identifies potential congestion by measuring increased latency in end-to-end packet transmission. Queue length-based detection monitors the buildup of packets in buffer queues, signaling high traffic load. Throughput-based detection looks for unexpected reductions in data delivery rates, which often indicate a congested network path. Additionally, Channel Busy Ratio (CBR) is used in the MAC layer to evaluate the level of channel utilization. CBR measures the proportion of time the wireless channel is sensed as busy within a given interval. A high CBR suggests heavy channel contention and potential congestion, especially in scenarios with dense vehicle communication. IoV network can dynamically adjust parameters such as transmission rate or message priority to eliminate congestion, by continuously monitoring the value of CBR. The integration of CBR with other detection techniques enhances the responsiveness and adaptability of congestion control strategies, which is vital for ensuring safe and seamless vehicular communication.

iii) Notification of congestion

Notification of congestion is the another critical part in congestion control, following the initial detection of congestion within the network. Once congestion is identified, whether through metrics such as CBR, round-trip time, queue length or throughput, it is important to inform the sender node so it can adjust its transmission behavior accordingly. This step ensures a coordinated response that helps alleviate network overload and maintain communication efficiency. There are two primary methods for notifying nodes of congestion, which are implicit and explicit notification. In implicit notification, the sender infers congestion based on indirect indicators, such as increased delays, packet losses or reduced acknowledgments. While this technique reduces communication overhead by avoiding additional control messages, it may result in delayed or less accurate reactions to congestion. On the other hand, explicit notification involves direct communication from intermediate nodes or the receiver to the sender, using control packets or dedicated header fields to convey congestion status. This approach provides more precise and timely feedback, allowing the sender to make informed adjustments to transmission rates or data prioritization. Although explicit mechanisms introduce additional signaling overhead, they often outperform implicit methods in highly dynamic and critical environments such as IoV network, where real-time responsiveness is essential for safety and performance.

iv) Algorithm of congestion avoidance

The congestion avoidance algorithm is activated at the source node whenever congestion is detected within the network. Its primary function is to mitigate congestion before it leads to severe packet loss or network instability. The algorithm initially responds by adjusting the flow rate at the transport layer, effectively controlling how much data is transmitted. This rate adjustment is not random or static; instead, it can be enhanced using optimization techniques to dynamically determine the most suitable transmission rate based on current network conditions.

The congestion control strategies can be adopted from a range of mechanisms as mentioned above to reduce the congestion in IoV network. This perspective is supported by multiple studies. Mishra et al. (2023) proposed an adaptive congestion control approach in IoV network where it reduces the risk of congestion at any intermediate node. It also saves energy by reducing packet drop due to buffer overwhelming. A cross-layer technique to controlling congestion in an IoV network based on throughput and buffer used was presented. The proposed model of congestion prevention between vehicles and RSUs, achieves better results in terms of throughput and packet success rate. Their IoV network model is evaluated based on various parameters that include packet success ratio (PSR), throughput in terms of link utilization, average length of buffer space occupied, variation of congestion window size. However, since the authors were focusing on V2I, they highlighted the issue of unsolved message flooding in V2V communication which is important to be considered and further discussed.

Roopa et al. (2022) provides an algorithm for traffic scheduling that maximizes vehicle flow at a road intersection while fostering social relationship between vehicles and RSUs. They put their focus for congestion avoidance and proposed a social network framework which enables social interactions (non-safety application) among all vehicles within the network or with any road infrastructure. The performance of the traffic conditions to optimize the traffic flow metrics such as traffic throughput, total travelling time, average waiting time, delay time, and service rate under different vehicle arrival rates were discussed between dynamic throughput maximization framework and adaptive traffic control algorithm. Nevertheless, the study has failed to consider the performance for V2V based communication.

Zhang et al. (2018) examined on how to handle periodic beacon message exchanges on control channel (CCH) and multicasting service messages on service channel (SCHs) for an IoV network. They outlined a scheme called PARCEL, which is based on priority aware congestion control, while taking into consideration the varying beacon message priorities for CCH safety applications. Multicasting and congestion control were enabled together in wireless communication board of the intelligent vehicle terminal architecture. The effectiveness of the proposed method was evaluated based on the parameters of average time interval and the number of vehicles. The simulation environment was constrained to a small-scale network with only 30 nodes, which does not fully reflect the complexity and density of real-world vehicular environments. As a result, the scalability and robustness of the proposed PARCEL scheme under high-density traffic scenarios (which can cause network congestion) remain uncertain. Moreover, the evaluation of the scheme focused primarily on average time interval metrics, without considering other important performance indicators such as packet delivery ratio, delay or throughput of the IoV network. Additionally, the impact of rapidly changing topologies due to high vehicular mobility was not comprehensively addressed, as it is a critical factor in IoV communication. These limitations suggest that while the proposed method is promising, further testing and refinement are necessary for deployment in large-scale, real-world networks.

In order to overcome the issues raised in the past studies, bio-inspired algorithms can be employed as an intelligent mechanism for congestion control, aiming to improve the overall performance and efficiency of the IoV network.

## 2.6 Bio-inspired Algorithm Optimization

Optimization is a technique for achieving the best results in a given situation or certain condition. From a computational standpoint, biologically inspired algorithms or known as bio-inspired algorithms are stochastic and metaheuristic search algorithms. They are useful for random resolving multimodal and distributed optimization issues such as the maximization of network utility, collaborative estimation in wireless sensor network (WSN), coordination of multiple agents in robotics, voltage control in power system etc. Bio-inspired algorithms have been known for optimization in recent decades due to their simplicity, flexibility and avoidance of local minima. It employs a robust search process that effectively preserves variety. In addition, bio-inspired algorithms have a higher probability of achieving globally optimal solutions and known flexible as one algorithm can be applied to different problems without much change in the structure of the algorithm (Poudel et al., 2023; Christaline et al., 2022).

The majority of its present research assumes that evaluating the objectives and limitations of prospective solutions is simple and inexpensive (Jin et al., 2018; Sarangi et al., 2016). Swarm based algorithms and evolutionary algorithms are the example of bio-inspired algorithms. Table 2.10 shows the taxonomy of bio-inspired algorithms.

Table 2.10
The Taxonomy of Bio-inspired Algorithms (Binitha & Sathya, 2012)

| **Bio-inspired Algorithms** | | |
|---|---|---|
| **Category** | **Algorithm** | **Inspiration** |
| Evolutionary | Genetic Algorithm (GA) | Darwinian theory |
| | Genetic Programming (GP) | Population computer programs |
| | Evolutionary Strategy (ES) | Theory of adaptation and evolution (mutation) |
| | Differential Evolution (DE) | Population-based differential search |
| Swarm based | Particle Swarm Optimization (PSO) | Social behavior of bird flocking |
| | Ant Colony Optimization (ACO) | Foraging behavior of ants |
| | Artificial Bee Colony Algorithm (ABC) | Behavior of bees |

Table 2.10 demonstrated the categories of bio-inspired algorithms which are evolutionary and swarms based algorithms. Evolutionary algorithms are inspired by the principles of natural evolution or called reproduction which are selection, mutation, recombination and survival of the fittest. GA is known as a prominent method in this category. It mimics the process of natural selection by representing alternative solutions as chromosomes. It the apply the genetic operators which are crossover and mutation to evolve better solutions over generations. GP extends the concept of GA by representing computer programs as tree structures, which enables automatic generation of code or symbolic expressions of the problem. Similarly to GA, ES prioritize mutation over crossover. It frequently use real-valued parameter representations. DE is another powerful method under evolutionary algorithms that works well especially for continuous optimization issues. It uses the differences between randomly selected individuals in the population to disturb the existing solutions, trailed by a selection procedure to identify the best candidates of the generation (Binitha & Sathya, 2012).

Conversely, swarm intelligence algorithms are based on the collective behavior of decentralized, self-organized systems in nature, such as bird flocks, fish schools, and insect colonies. PSO algorithm is based on the movement and intelligence of swarms, where particles regulate their positions in the search space based on their own experiences and those of neighboring particles. ACO algorithm models the foraging behavior of ants, where artificial ants search for optimal paths by laying down and following pheromone trails, making it suitable for combinatorial optimization problems such as routing and scheduling. ABC algorithm is inspired by the food foraging behavior of honey bees, where bees are categorized as employed, onlooker, or scout bees, each playing a role in exploring and exploiting food sources or called as solutions (Selvaraj et al., 2014).

Although both evolutionary and swarm-based algorithms are effective in solving optimization problems, swarm intelligence algorithms are often superior in terms of convergence speed, simplicity, and adaptability to dynamic environments. EAs such as GA and GP rely on complex operations such as crossover and mutation, which can lead to slower convergence and require a proper parameter tuning. They also depend heavily on selection pressure, which can cause premature convergence or loss of diversity. In contrast, swarm-based algorithms such as PSO, ACO and ABC utilize cooperative behavior and information sharing among individuals (particles, ants, or bees), which often leads to faster discovery of optimal or near-optimal solutions. These algorithms are less reliant on disruptive operations and more focused on gradual, intelligent exploration of the search space. Additionally, swarm algorithms tend to be more scalable, easier to implement, and more robust in handling high-dimensional, nonlinear, and multi-modal optimization problems. As a result, in many real-world applications such as feature selection, neural network training, network optimization and dynamic scheduling, swarm-based algorithms frequently outperform traditional evolutionary methods in terms of efficiency, precision, and reliability.

### 2.6.1 Genetic Algorithm (GA)

Despite all the EAs discussed in the previous section, Genetic Algorithm (GA) is identified as the most frequently employed for vehicular network optimization. GA is a population genetics-based adaptive heuristic search tool and categorized as the global search heuristics. The classical terminology of GA is providing a solution for the problem underneath consideration. It is known as an individual; a group of individuals are called population. Each individual has a single chromosome string that encodes their data features. A chromosome is a collection of alleles that each represent one quantum of information, such as a bit, digit, or letter, and requires coding and decoding in order to exchange solutions with the nominal object space. GA methodology involves population initialization, selection of the individuals according to their fitness value, reproduction (crossover and mutation) of the selected individuals to create new offspring, and the termination once the most optimized result is found (Kumar, Husaian, Upreti & Gupta, 2010). Figure 2.19 shows the flowchart of GA process.

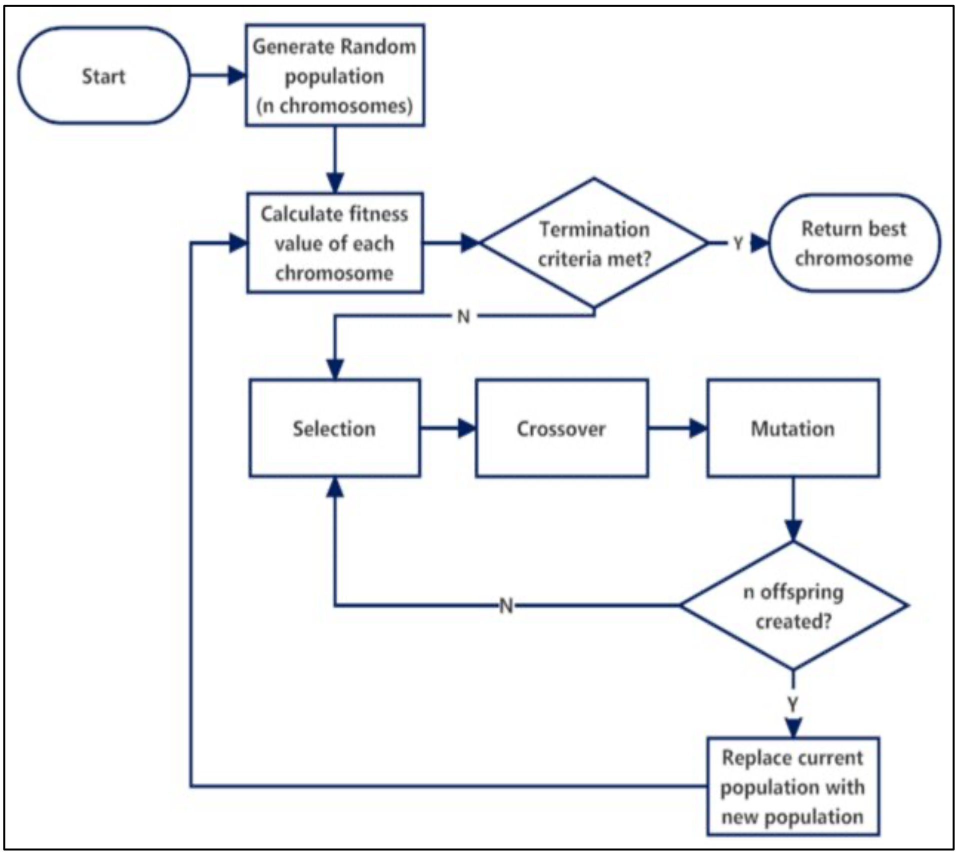



Figure 2.19 The Flowchart of the Process of GA (Kang & Ye, 2021; Zarzar, 2006)

Among ranges of GA applications for optimization purpose include fuzzy controller pressure system (Liang, Zou, Zuo & Khan, 2020), household level hybrid renewable energy system (Mayer, Szilágyi & Gróf, 2020), traffic control optimization (Mao, Mihˇaitˇa & Chen, 2021), travelling salesman problem (Juneja, Saraswat, Singh, Sharma, Majumdar & Chowdhary, 2019), data classification (Syarif, Prugel-Bennet & Wills, 2016), medicine (radiology, radiotherapy, oncology, paediatrics, cardiology, endocrinology, surgery, gynaecology etc.) (Ghaheri, Shoar, Naderan, & Hoseini, 2015), image processing (Tian, Li, Yang & Liang, 2018; Boyat & Joshi, 2015) and scheduling (Ladj, Varnier & Tayeb, 2016).

In terms of the implemtation of GA in vehicular network related optimization, traffic signal optimization was introduced by (Mao, Mihˇaitˇa & Chen, 2021) with the aim of minimizing travel time of the users. The authors performed the optimization at the intersections which is the main reason of traffic congestion in the city of Sydney, Australia. This method is proven to save travel time by 45% and produce low computational time as Machine Learning (ML) was used to simulate the traffic model. Figure 2.20 shows the GA optimization model proposed by (Mao, Mihˇaitˇa & Chen, 2021).

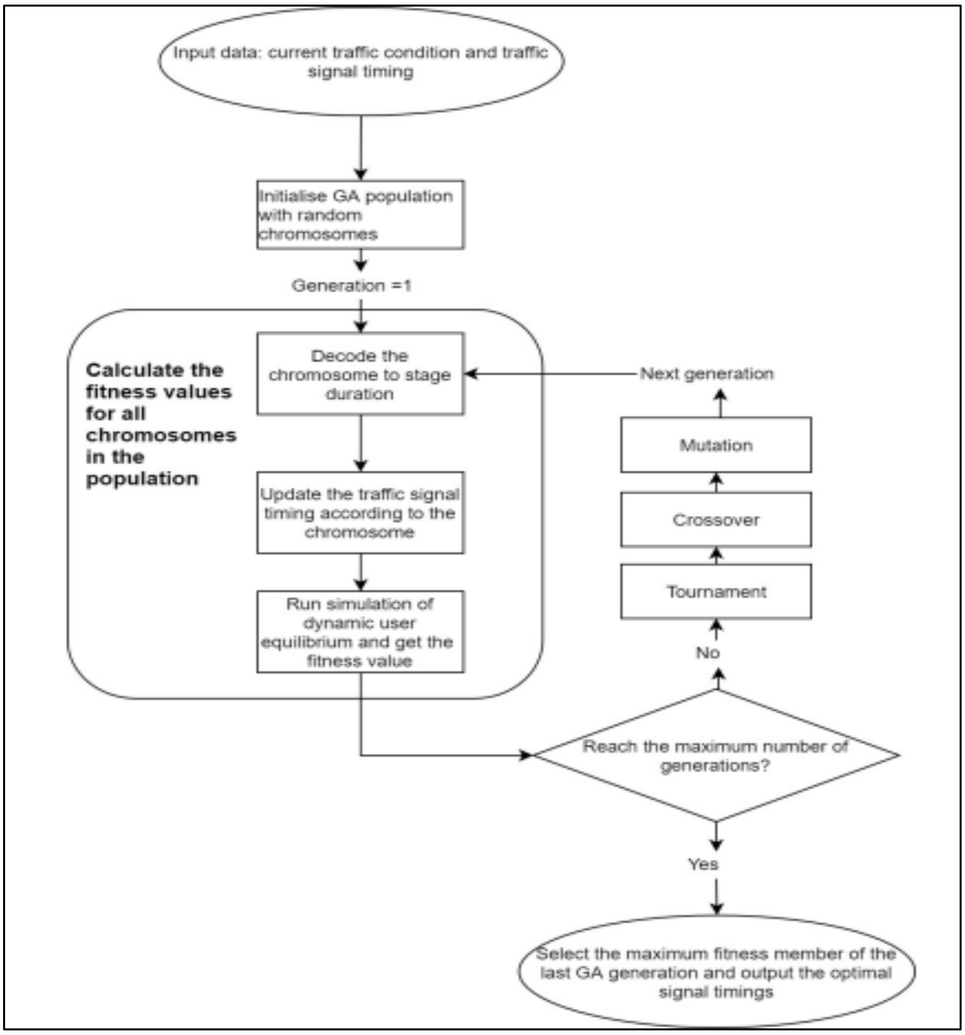



Figure 2.20 GA Optimization Model (Mao, Mihˇaitˇa & Chen, 2021)

However, in order to complete the GA optimization, a gap is found in the study in terms of the delay time especially in peak operational hours (Mao, Mihˇaitˇa & Chen, 2021). Meanwhile, another limitation of GA for phase duration optimization with a large spectrum of values is the unlimited number of combinations that can appear specifically if the scale of the traffic network is extended (Mao, Mihˇaitˇa & Chen, 2021). In other words, the function GA becomes limited towards network scalibility. The algorithm has difficulties in dealing with dynamic data sets which make it less suitable to be used to optimize IoV network.

### 2.6.2 Particle Swarm Optimization (PSO) Algorithm

Particle Swarm Optimization (PSO) algorithm is a population-based optimization technique which is inspired by social behaviour of bird flocking or fish schooling. This bio-inspired algorithm was proposed by Kennedy and Eberhart back in 1995 (Cai, Huang, Peng & Xu, 2020). Owing several added value points such as quite insensitive to scaling of design variables, simple implementation, easily parallelized for concurrent processing, derivative free, very few algorithm parameters, and very efficient global search algorithm, PSO algorithm is promising to be used and solve various optimization problems. The algorithm adjusts its search direction based on both individual and group experience, enabling quicker convergence without sacrificing solution quality (Cai et al., 2020). The basic PSO algorithm is illustrated in Figure 2.21 (Li, Sun & Hou, 2021).

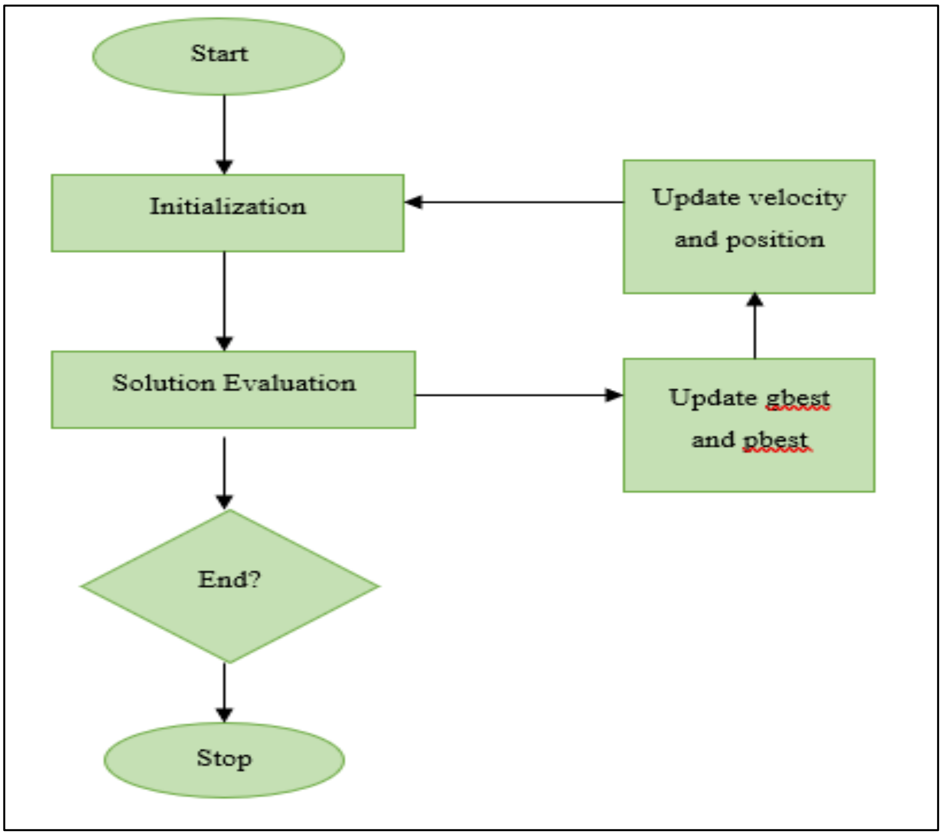



Figure 2.21 Basic PSO Algorithm (Li, Sun & Hou, 2021)

Figure 2.21 illustrates the basic PSO algorithm, a population-based stochastic optimization technique inspired by the social behavior of birds flocking or fish schooling. The algorithm is widely used in solving optimization problems due to its simplicity and effectiveness. PSO algorithm consists of a swarm of bird-like particles. Each particle resides at a position in the search space. It owns a fitness function whereby it will define the fitness of each particle, representing the quality of its position. The particles move over the search space with a certain velocity. Each particle has an internal state with network of social connections. Besides, the velocity is dependent on its own best position found so far called *pbest*, the best solution that was found so far by its social neighbours known as lbest and the global best so far named *gbest*. The swarm will converge to its optimal positions (Li, Sun & Hou, 2021; Cai et al., 2020).

Past studies have shown that PSO algorithm have been implemented in various domains; neural network training (Cai et al., 2020), reactive power optimization of electric power system (Tianhong, Guili, Lei & Tong, 2014), target tracking for monitoring system (Ding & Fang, 2018), travelling salesman problem (Rokbani, Kumar, Abraham, Alimi, Long, Priyadarshini & Son, 2021; Gulcu & Ornek, 2019), optimization design of electromagnetic relay (Jiang, Wang, Yuan, Luo, Yu & Duan, 2018), routing optimization (Cong, Xie & Gao, 2017), clustering, offloading and bandwidth allocation (Lin & Zhang, 2022; Khan et al., 2018), and congestion control in vehicular network (Panimalar & Jacob, 2020; Zhang, Zhou, Lv & Jiao, 2019; Royyan, Ramli, Lee & Kim, 2018).

Focusing on the application of PSO algorithm for congestion control, it is applicable in managing congestion in wireless sensor networks (WSN) (Panimalar & Jacob, 2020; Zhang et al., 2019; Royyan et al., 2018). The authors, Panimalar and Jacob (2020) stated that the congestion in WSN is occured due to the possibility of blocking of packet or insufficient queue size. This situation happened when there is an inadequate obtainability of space (topology) which consequently causing degradation of the network performance. They opted PSO algorithm to optimize the optimal allowable data rate, based on the speed of the nodes (small scale of WSN). On the other hand, Royyan et al., (2018) configured a PSO solution for large scale WSN. The particles in the PSO algorithm search a solution with the objective of minimizing the QoS metric, which is packet delay as much as possible. The outcomes of the research confirmed that the suggested scheme guarantees the traffic is free of congestion and maintains fairness among the sensor nodes. Besides, due to the characteristic of the efficiency as a global search algorithm, it has a high potential in achieving the global optimum solution. It is proven to be outperformed as it transmitted a packet load without causing network congestion. Meanwhile, Elhabyan et al. (2014) proposed a novel centralized PSO protocol for Hierarchical Clustering (PSO-HC) in WSN. Their goal is to use two-hop communication between the sensor nodes and their respective CHs in order to maximize network scalability and maximize network longevity by decreasing the number of active CHs. They evaluated their scheme based on average consumed energy and throughput.

Furthermore, PSO algorithm also have been successfully implemented in optimizing VANETs for various purposes (Termunikar, 2022; Murugan et al., 2020; Samara & Alhmiedat, 2014). Termunikar (2022) proposed a PSO algorithm which enable multi-hop technique with the objective to select the best route, find the stable CH and remove the malicious node from the network in order to avoid false message delivery. They performed clustering of the same group of nodes into groups. The proposed scheme shows an increment of 20% in terms of the PDR compared to the non-optimized VANETs. Samara and Alhmiedat (2014) anticipated an intelligent emergency message broadcasting in VANET using PSO algorithm to assist the VANET system in meeting its safety objectives in an efficient and intelligent manner, enabling the quick and efficient distribution of emergency signals within a given geographic area.

Murugan et al. (2019) discussed the design of the MANET and VANETs infrastructure with the help of PSO algorithm parameter design. PSO algorithm was chosen because it is able to determine and choose the optimal combination of parameters. In addition, the algorithm responds better to changes in the network topology thus reducing the variance of the intended output. As a result, it reduced the packet delivery delay which then directly leads to less packet loss and attenuation.

On the other hand, Liping et al. (2020) introduced a combination of PSO algorithm and quantum behavior named Quantum Particle Swarm Algorithm (QPSO) to resolves the majorization problem related to available transmission capacity (ATC) for power grid system. With the aid of PSO algorithm, their proposed QPSO algorithm is proven to have strong global search ability, which resulting in excellent performance and faster convergence speed.

### 2.6.3 Ant Colony Optimization (ACO)

Another optimization algorithm used for tackling challenging combinatorial optimization issues is called ant colony optimization (ACO). The behaviour of real ants, who employ pheromones as a means of communication, in which pheromone trails are laid and followed, serves as the inspiration for ACO. ACO is based on indirect communication within a colony of simple agents, called (artificial) ants, mediated by (artificial) pheromone trails, similar to the biological example. It had a crucial influence in encouraging additional investigation into a wide range of various challenges and algorithmic variants that provide significantly improved computational performance. The algorithm of ACO involves several important steps; i) setting up parameters; ii) initialize pheromone for each region; iii) create region; iv) determine the objective function for the problem; v) check the condition of the region (repeating process); vi) obtain the local optimum value. The flowchart is shown in Figure 2.22.

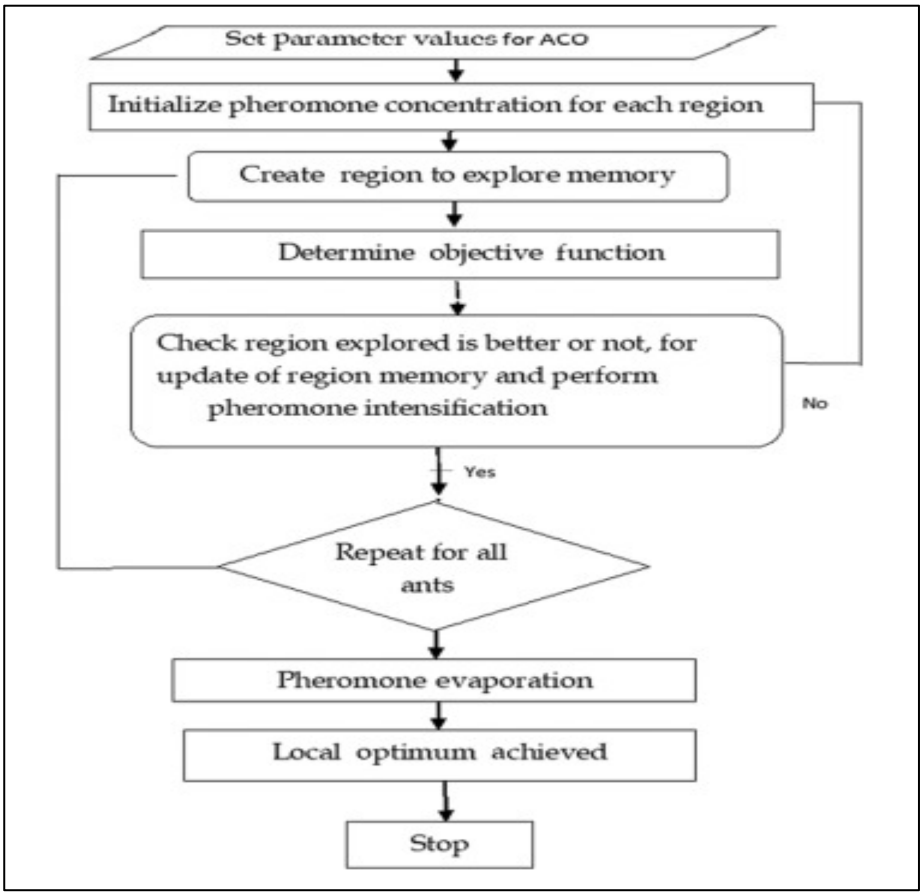



Figure 2.22 Fundamentals of ACO Algorithm (Dorigo & Stützle, 2018)

Figure 2.22 illustrates the fundamental principles of the ACO algorithm, which is inspired by the foraging behavior of real ant colonies. In this algorithm, artificial ants traverse a solution space by probabilistically selecting paths based on pheromone trails, which are updated iteratively to reinforce high-quality solutions. The figure typically depicts key components such as pheromone initialization, solution construction, pheromone updating, and convergence mechanisms, all of which contribute to the ability of the algorithm to solve complex optimization problems.

This foundational structure has enabled ACO to achieve world-class performance across a wide range of applications. As highlighted by Deng, Xu and Zhao (2019) and Dorigo and Stützle (2018), ACO has been successfully applied to problems such as wireless sensor networks, sequential ordering, scheduling, assembly line balancing, probabilistic traveling salesman problems (TSP), 2D-HP protein folding, DNA sequencing, protein–ligand docking and packet-switched routing in Internet-like networks. These diverse applications underscore the algorithm’s adaptability and effectiveness in solving combinatorial and dynamic optimization challenges.

However, despite its versatility, ACO faces inherent limitations when scaled to large and complex environments, particularly in the context of vehicular communication systems. The computational overhead and convergence delays associated with large-scale optimization can hinder its real-time applicability in Internet of Vehicles (IoV) scenarios, where rapid decision-making and low-latency communication are critical. As such, while Figure 2.22 captures the core mechanics of ACO, its practical deployment in vehicular networks requires further refinement to overcome scalability and performance constraints.

### 2.6.4 Artificial Bee Colony (ABC) Algorithm

The Artificial Bee Colony (ABC) algorithm is a swarm intelligence-based optimization method. The model is based on the foraging behavior of honeybee colonies. In this algorithm, the search for optimal solutions is performed by three types of artificial bees, which are employed bees, onlooker bees, and scout bees. Each type of bees have their specific role and they work together with each other. First, the employed bees explore specific solutions or called food sources and share the quality of these solutions with onlooker bees in the hive. Onlooker bees then probabilistically choose among the shared solutions based on their fitness. Meanwhile, the scout bees randomly explore the search space to discover new potential solutions (Alaidi et al., 2021). This division of labor allows ABC algorithm to balance exploration and exploitation, making it effective for solving complex optimization problems such as scheduling, vehicle routing problem in vehicular network, management of energy for mobile devices and travelling salesman problem (Comert & Yazgan, 2023; Alaidi et al., 2021). The pseudocode for the algorithm is illustrated in Figure 2.23.

1. Initialization phase
2. REPEAT
3. Employed Bees Phase
4. Onlooker Bees Phase
5. Scout Bees Phase
6. Memorize the best solution achieved so far.
7. UNTIL (Cycle = Maximum cycle number or maximum CPU time)

Figure 2.23 ABC Algorithm (Alaidi et al., 2021)

ABC algorithm was preferred to be applied in solving the problem in vehicular routing. The study by (Comert & Yazgan, 2023) presents a novel hierarchical hybrid algorithm by integrating ACO and ABC algorithms to address multi-objective Electric Vehicle Routing Problems (EVRPs). This approach aims to optimize multiple conflicting objectives simultaneously, such as minimizing travel distance, energy consumption, and operational costs, while considering constraints such as battery capacity and charging station availability. In the first phase, ACO is employed to generate an initial solution. Local search algorithms and simulated annealing were integrated to enhance the quality of the solution, as well as to reduce computation time. As for the second phase, the authors utilizes ABC algorithm to refine the initial solution obtained from ACO. The algorithm simulates the foraging behavior of honey bees to explore the solution space effectively, balancing exploration and exploitation to prevent local optima. Weighted Sum Method (WSM) and the Conic Method (CM) scalarization methods were applied in order to handle the multi-objective nature of EVRPs. As a result, the proposed approach demonstrates improved performance compared to existing EVRPs where it obtain the best-known results in most instances. Moreover, the algorithm is applied to a real-life case study, further validating its practical applicability and robustness in solving complex EVRPs. However, while the hybrid ACO-ABC algorithm outperform on benchmark datasets and a real-life case, its computational complexity and performance on very large-scale networks have not been thoroughly tested. The study also raised an issue in the dependency of scalarization methods. The use of WSM and CM to convert multi-objective problems into single-objective ones may limit the diversity of solutions and the exploration of trade-offs between conflicting objectives. Since the components of both ACO and ABC algorithms rely on fine parameter tuning, improper tuning can lead to suboptimal results which also will cause degradation in the performance of the proposed approach.

On the other hand, the ABC algorithm was likely to be implemented in solving large-scale instances of the urban transit routing problem. Zervas et al. (2024) presents a hybrid metaheuristic approach to address the Urban Transit Routing Problem (UTRP). This problem involves designing efficient public transportation routes that minimize passenger travel time and the number of transfers. The authors proposed an algorithm that combines the global search capabilities of the ABC algorithm with the local refinement strength of the Hill Climbing (HC) method. The algorithm is implemented in a parallel computing environment to enhance computational efficiency. It allows simultaneous exploration of multiple solution spaces. The approach was tested on various large-scale benchmark instances, demonstrating its effectiveness in generating high-quality transit routes. Nevertheless, the performance of the algorithm was not extensively evaluated in relation to extremely large scale network or real-time dynamic scenario, thus its scalability remains uncertain.

In accordance with the discourse, the algorithm is identified to be known for its simplicity, flexibility and ability to avoid local optima. However, it may converge slower compare to other bio-inspired algorithms in certain scenarios make it least preferable as a congestion control scheme for IoV network .

### 2.6.5 Bio-inspired Algorithms for Vehicular Network Optimization

Table 2.11 presents a qualitative comparison of the bio-inspired optimization algorithms discussed in this study. The comparison highlights key attributes such as convergence speed, robustness, parameter tuning, scalability and adaptability to dynamic environments.

Table 2.11
Qualitative Comparison of GA, PSO, ACO and ABC Algorithms (Dan et al., 2019)

| **Characteristics** | **GA** | **PSO** | **ACO** | **ABC** |
|---|---|---|---|---|
| Convergence speed | Moderate | High | Slow | Slow |
| Nature | Discrete | Continuous | Discrete | Continuous |
| Global optimization | High | High | Moderate | Moderate |
| Parameter tuning | Complex | Simpler | Complex | Complex |
| Adaptability in vehicular network | Moderate | High | High | Moderate |
| Scalability | Complex | Good | Can be heavy (for large graphs) | May degraded due to problem size |
| Memory usage | High due to parameter tuning | Low | High due to pheromone matrix | High due to fine parameter tuning |

Based on the discussion of the bio-inspired algorithms features in Table 2.11, it is identified that PSO algorithm is considered as the best optimization suitable to be opted in this research since it is proven to has the highest potential of global optimization and convergence rate compared to the other algorithms, especially in vehicular adhoc environment.

PSO algorithm has exhibited greater effectiveness compared to GA in network optimization tasks. The velocity-based search approach of the algorithm facilitates faster convergence by directing each particle towards its individual optimum and the global optimum solution. This memory-driven search methodology yields enhanced stability and efficiency in optimization. Conversely, GA depends on stochastic crossover and mutation, potentially hindering convergence and inducing instability (Yun et al., 2022). Moreover, the computational simplicity of PSO algorithm and its inherent capability for continuous optimization make it suitable for dynamic network situations that require rapid flexibility and minimal overhead. These benefits shows that PSO algorithm is a better option than GA for optimizing vehicular and wireless networks.

On the other hand, PSO algorithm offers several benefits over ACO algorithm in the context of vehicular network optimization, particularly within dynamic and real-time environments. PSO algorithm exhibits faster convergence due to its velocity-based update mechanism, which enables rapid adaptation to changing network topologies. It is considered as an essential requirement in vehicular networks. Unlike ACO, which relies on pheromone trails that require multiple iterations to stabilize, PSO achieves efficient optimization with lower computational overhead. Furthermore, PSO is inherently suited for continuous optimization problems for example congestion control, bandwidth allocation and power control. Meanwhile, ACO is traditionally designed for discrete combinatorial tasks. The simplicity of parameter tuning and lower memory requirements, making it a more practical and scalable choice for real-time vehicular applications. These characteristics collectively position PSO algorithm as a more suitable algorithm in comparison to ACO algorithm for network optimization in IoV scenario where speed, adaptability and computational efficiency are critical (Dan et al., 2019; Binitha & Sathya, 2012). These features are considered extremely important aligned with the purpose of eliminating traffic network congestion.

PSO algorithm also typically surpasses the ABC algorithm in network optimization applications due to its accelerated convergence, superior exploitation of optimal solutions and more straightforward parameter tuning. The velocity-based update mechanism of the algorithm facilitates effective and reliable optimization, especially in continuous domains such as transmission rate, bandwidth allocation, routing and QoS management. In contrast to ABC algorithm, which allocates tasks among employed, observer, and scout bees exhibiting stochastic search behaviour, PSO algorithm is dependent on collective learning through personal and global best, making it more precise and adaptable to extensive and dynamic network environment (Dash et al., 2021). These benefits provide PSO algorithm as a more appropriate and effective option for optimizing contemporary networks, including IoV network, cloud computing and wireless sensor system.

## 2.7 Related Works on Bio-inspired Algorithm based IoV Network Optimization

Bio-inspired congestion control scheme through optimization was used as a basis to design a robust, scalable and decentralized vehicular network (Royyan et al., 2018). The purpose of the network optimization is to reduce congestion in a dense network. This section discusses the past works of bio-inspired based IoV network optimization and the parameters that were examined by previous researchers in align to the implementation of this research, illustrated in Table 2.8.

Rawat et al., (2017) proposed adjustments of the contention window size at the

MAC layer to increase throughput and reducing delay. They introduced a hash-based detection for data falsification attack for trustworthiness of message. The size of the contention window was modified in order to send quick and accurate information to the neighboring vehicles. The authors also presented a clustering approach which is considered as a solution towards traffic congestion with the purpose to reduce travel time of the road users. The mobility scenario was presented as “inchworm” where every approaching group of vehicles will need to reduce their speed, and all of them will need to wait until they have slowly passed the root cause point of the traffic. As a result, vehicles could make informed decision to reduce their waiting time when accurate information is transmitted to them. However, their work paid limited attention to critical network metrics such as throughput and delay, which are very important for evaluating congestion control performance.

Another work that focusing on the similar technique of clustering as Rawat et al. (2017), is introduced by Khan et al. (2018). The authors mentioned Moth Flame Clustering Algorithm for IoV (MFCA-IoV). A Cluster Head (CH) oversees all intra- and inter-cluster communication in a cluster. Basically, the main focus of this method is on evaluating the parameters of dynamic transmission-range, ideal degree, mobility pattern, dynamic grid sizes, dynamic number of nodes, speed and direction. Nonetheless, the approach still showed vulnerability to the problem of local optimum, which can affect global performance.

The stability of the IoV network topology is also raised concern in the area. Aadil et al. (2018) proposed a metaheuristic dragonfly-based clustering algorithm (CAVDO) which is used for cluster-based packet route optimization. The CAVDO algorithm is used together with mobility aware dynamic transmission range algorithm (MA-DTR) for transmission range adaptation on the basis of traffic density. The parameters that were considered to measure the performance of the proposed algorithm are number of un-clustered nodes as a re-clustering criterion, clustering time, re-clustering delay, dynamic transmission range, direction, and speed. Although it minimized the number of clusters and showed improvement in several scenarios, the method still had potential for further enhancement in terms of efficiency and reliability.

Performance evaluation of IoV network that structured the joint approach optimized offloading decision, offloading ratio, and resource allocation (ODRR) to minimize delay is addressed by Lin & Zhang (2022). An offloading decision-making algorithm was developed based on PSO algorithm. In the proposed work, the particles have only two attributes which are speed and position. Speed represents the level of movement and position represents the direction of particles. Though the proposed method is promising, yet it faced a notable limitation which is the possibility of task failure due to unreliable transmission links or edge node failures, which compromises system robustness.

On the other hand, Zhang et al. (2022) presented a bandwidth aware multi domain virtual network embedding algorithm (BA-VNE) in order to solve the problem of resource scheduling in IoV network. The algorithm is primarily intended for the problem which require users to have high bandwidth in wireless communication mode. Link bandwidth, mapping cost and virtual network request (VNR) acceptance rate are the metrics evaluated to verify the effectiveness of the proposed work. Although it successfully ensured maximum bandwidth utilization, it introduced significant complexity due to the involvement of multiple domains. The solution is identified to be less practical for real-time or large-scale deployment. Table 2.12 summarize the PSO-based IoV network optimization.

Table 2.12
Summary of PSO-based IoV Network Optimization

| **Authors** | **Year** | **Approach** | **Optimization Parameter(s)** | **Result** |
|---|---|---|---|---|
| Rawat et al. | 2017 | Clustering approach (hash-based detection) to reduce users' travel time on the road, in case traffic congestion occurs. | Contention window size and cluster formation parameters. | Laid consideration on throughput and delay performance and it is not the focus of the research. Both are evaluation metrics, not optimization variables. The actual optimized variable is contention window size + cluster-based decision-making. |
| Khan et al. | 2018 | Moth flame clustering algorithm (MFCA-IoV) to generate optimized clusters for transmission. | Algorithm decides optimal Cluster Heads (CHs) based on transmission range, mobility, speed, and direction | They optimize clustering parameters (CH selection, range, node mobility factors). Provide better result where 73% nodes are not selected as CH. The limitation is susceptibility to local optimum. |
| Aadil et al. | 2018 | Metaheuristic dragonfly-based clustering algorithm (CAVDO) for cluster-based packet route optimization. | Number of clusters and routing path. | Their optimization targets number of clusters and routing path efficiency, which indirectly affects delay and PDR. |
| Lin & Zhang | 2022 | Offloading strategy problem of multiuser and multi-objective nodes using PSO based joint optimization approach. | Offloading decision, resource allocation by RSU, offload ratio by vehicles | Possibility of task failure caused by transmission link or edge node failure. |
| Zhang et al. | 2022 | Allocation of bandwidth resources using multi-domain Virtual Network Embedding Algorithm (VNE) in IoV network. | Bandwidth allocation and virtual node embedding. | Ensure maximum bandwidth, but complex due to the involvement of multiple domains. |

While Table 2.12 highlights the potential of PSO and other bio-inspired algorithms for IoV network optimization, it also reveals several important limitations that motivate the present study. Most existing works primarily focus on clustering mechanisms, task offloading strategies, or bandwidth allocation, where throughput, PDR and delay are largely treated as performance evaluation metrics rather than direct optimization objectives. Furthermore, many approaches optimize parameters such as cluster head selection, offloading ratios, routing paths, or virtual network embedding, which do not explicitly address real-time congestion control and communication reliability in highly dynamic vehicular environments. In addition, issues such as premature convergence to local optima, high computational complexity and limited scalability restrict the applicability of these methods in dense traffic scenarios and rapidly changing network conditions.

To address these limitations, the present study proposes a PSO-based optimization framework that directly targets communication-level parameters, specifically the transmission rate and channel busy ratio (CBR). By dynamically adjusting the transmission rate according to real-time channel conditions, the proposed approach aims to regulate channel utilization and mitigate congestion more effectively. This strategy enables simultaneous improvement in throughput, PDR and delay while maintaining channel stability under varying vehicle densities and temporal traffic patterns. Consequently, the proposed framework offers a more adaptive, scalable and practical solution for IoV communication compared to existing approaches summarized in Table 2.12.

Addressing these research gaps, this study integrates the PSO algorithm within the IoV network to manage congestion during safety message dissemination and to enhance overall communication performance. The primary goal is to maximize throughput and PDR while minimizing delay, which is a critical requirement for safety-critical vehicular applications. In this work, delay is adopted as the objective function in the PSO-based optimization process, as it directly reflects the timeliness of message delivery and the ability of the network to support real-time decision-making. By minimizing delay, the PSO algorithm guides the network toward optimal transmission configurations that improve communication efficiency and responsiveness. Through its adaptive swarm behavior, the PSO algorithm enables the network to dynamically respond to variations in vehicle density, network topology and channel conditions. As a result, the optimized IoV network achieves higher data delivery reliability, lower latency and improved responsiveness, making it more suitable for real-world vehicular communication scenarios.

## 2.8 Summary

This chapter provides a summary, evaluation, and critical analysis of previous research efforts on PSO-based optimization in IoV network. Through an in-depth examination of the optimization strategies proposed by various researchers, it becomes evident that there remains a pressing need to develop a more efficient and adaptive IoV network. Specifically, bio-inspired algorithms have emerged as promising solutions due to their robust, flexible and intelligent nature by mimicking biological behaviors to solve complex optimization problems. Their inherent capability to perform global searches and adapt to dynamic environments makes them highly suitable for addressing the challenges of vehicular networks. Bio-inspired algorithms provide robust and flexible approaches for tackling various complex problems by mimicking the adaptive and intelligent behaviors observed in nature. Their ability to perform global search and adapt to dynamic environments makes them valuable tools in various areas.

In light of this, this research proposes an efficient PSO-based optimization approach to enhance the transmission of safety messages in IoV network. While several optimization techniques have been explored in the literature, they often fall short in addressing key QoS parameters such as throughput, delay and packet delivery ratio (PDR). These parameters are critical for ensuring reliable and timely communication, especially in dense and dynamic vehicular environments.

Furthermore, although previous methods have demonstrated reasonable performance, they frequently overlook the optimization of QoS metrics and tend to neglect the issue of network congestion, an aspect which is exremely crucial for improving the overall efficiency and scalability of IoV network. The following chapter details the research methodology employed to address these gaps and to achieve the objectives of this study.

# CHAPTER 3
# RESEARCH METHODOLOGY

## 3.1 Introduction

There has been increasing interest in research and projects in the adoption of traffic congestion in the IoV environment. This research aims to make a contribution towards alleviating traffic congestion by managing the information dissemination among the vehicles in IoV network for congestion free network with low latency, high throughput and high packet delivery based on the optimization of the network . This chapter presents the research methodology of this thesis, consists of literature review, the problem formulation, the research design followed by the procedures formulated to fulfil the research objectives.

The research process began with a detailed elaboration on the literature review in the field of vehicular network which leads towards the problem identification. Once the problem was formulated, the experimental design and development is explained. Next is the development of the proposed model where a traffic and network simulation setup of IoV network model of urban city scenario is performed.

In particular, the work involves the proposal of the optimized IoV network as a congestion control mechanism and algorithm by maintaining the efficiency of the network, distributing safety messages to the neighbouring vehicles. PSO algorithm is used to optimize the data transmission rate of the IoV network.

Finally, the performance of the proposed optimization mechanism is evaluated in vehicular states. Three QoS performance metrics are selected for the evaluation purpose, which are the throughput, the packet delivery ratio (PDR) and delay. The overall research process is illustrated in Figure 3.1.

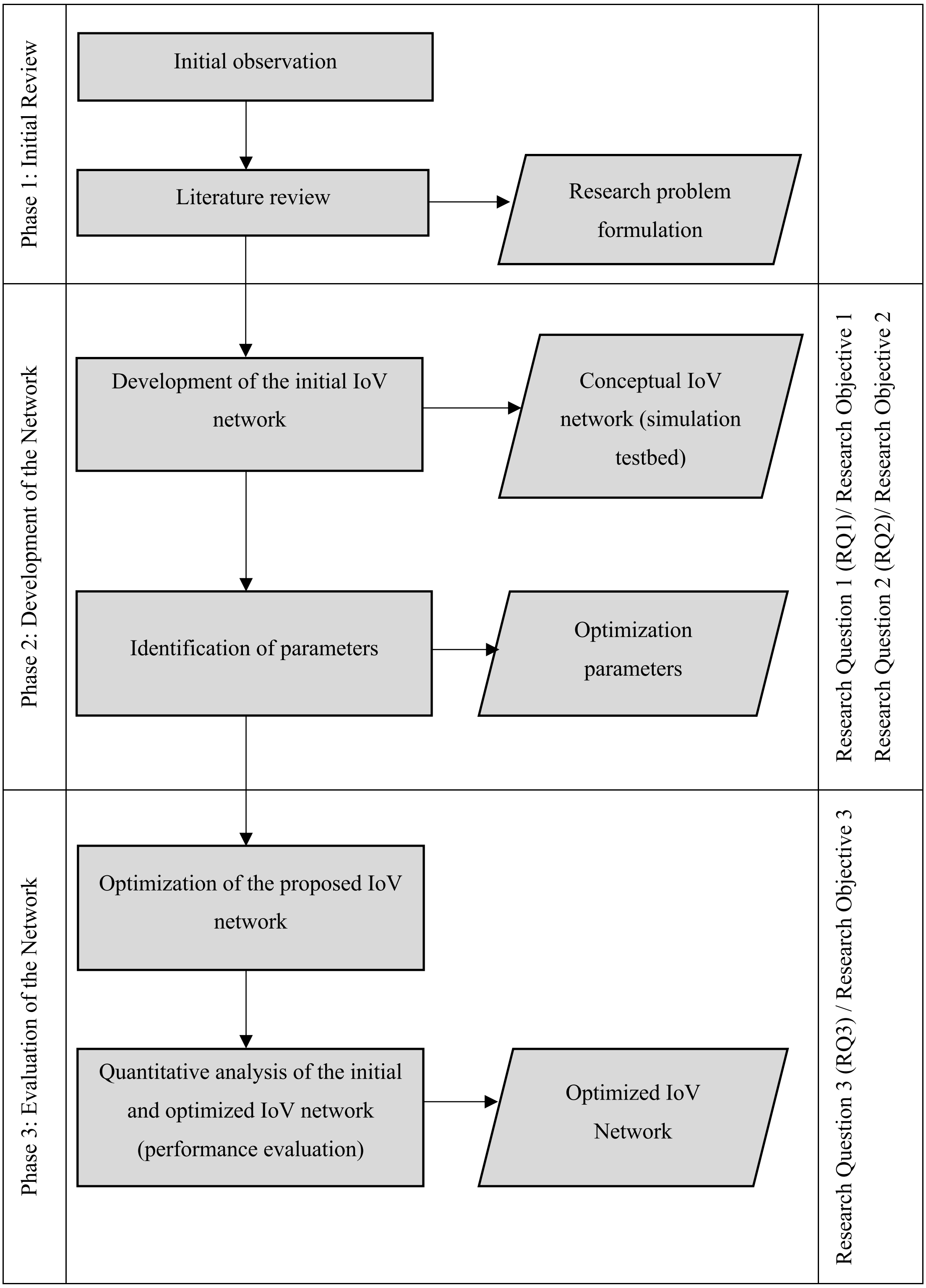


Figure 3.1 Overview of the Research Process

Figure 3.1 explains the research process in this study. The first phase consists of a comprehensive review of relevant literature, existing standards and mobility models related to IoV networks, with particular emphasis on congestion control, safety message dissemination and communication delay. Delay, often referred to as end-to-end latency, represents the time taken for a message or packet to travel from the source vehicle to the intended receiver. In dense vehicular environments, delay can significantly impact the timeliness and reliability of safety-critical messages, such as collision warnings or emergency braking notifications. Chapter 2 highlighted several studies that show excessive delay can lead to late reception of warning messages, reducing their effectiveness and potentially compromising road safety. By focusing on delay in the literature review, this study identifies key factors influencing latency, including channel congestion, transmission rate, network load and vehicle mobility patterns. Understanding these factors provides the theoretical foundation for optimizing the IoV network, ensuring that messages are delivered both reliably and within acceptable time constraints.

The second phase involves the design and development of the proposed optimized IoV network architecture. This phase addresses Research Question 1 (RQ1) / Research Objective 1 (RO1), which focuses on identifying the critical parameters that affect congestion control, such as channel busy ratio (CBR), throughput, packet delivery ratio (PDR), delay, and transmission rate. Among these parameters, delay is particularly important because it directly impacts the effectiveness of safety message dissemination. High network delay can cause safety messages to arrive too late, negating the purpose of real-time communication in vehicular networks. Based on the findings from Phase 1, the conceptual IoV framework is formulated, outlining network layers, communication protocols, and congestion control mechanisms designed to minimize delay while maintaining high throughput and reliability. Moreover, this phase further addresses Research Question 2 (RQ2) / Research Objective 2 (RO2), which examines how the optimized IoV network can be constructed to mitigate congestion and enhance communication performance. The network is modelled and implemented using simulation tools incorporating a PSO-based optimization mechanism. This mechanism dynamically adjusts the transmission rate and other network parameters to reduce channel congestion, thereby lowering delays and improving the timeliness of message delivery. The output of this phase is the set of optimization parameters that balance network load, maximize PDR, and ensure that delays remain within acceptable thresholds for safety-critical communication.

The final phase focuses on evaluating the performance of the proposed optimized IoV network against a non-optimized baseline scheme. This phase addresses Research Question 3 (RQ3) / Research Objective 3 (RO3), which investigates the extent to which the optimized network improves communication performance under varying traffic and network conditions. Extensive simulations are conducted to measure key performance indicators, including throughput, PDR and delay. Delay is emphasized because it serves as a direct indicator of network responsiveness, and its reduction is crucial for ensuring that safety messages are disseminated in real time. The findings are analysed to validate the effectiveness of the proposed congestion control mechanism, demonstrating that optimizing network parameters particularly the transmission rate, significantly reduces delay, improves reliability and enhances the overall safety of IoV communication in dense vehicular environments.

The research process described above establishes the foundation for the subsequent operational framework. The operational framework translates these phases into practical procedures, defining the structure, workflow and mechanisms through which the proposed optimized IoV network is implemented and assessed. The operational framework is illustrated in Figure 3.2.

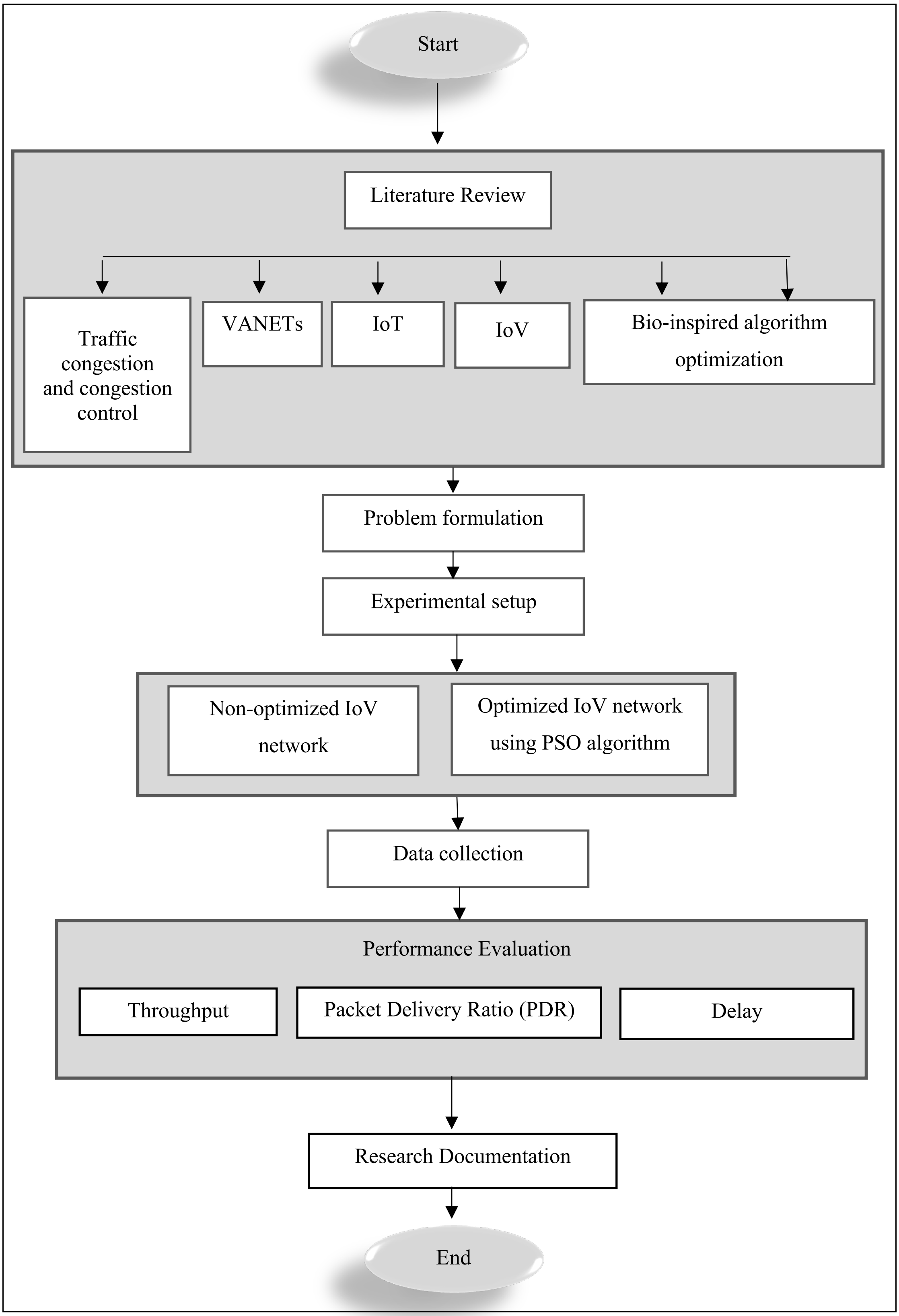


Figure 3.2 Operational Framework

## 3.2 Operational Framework

Figure 3.2 depicts the operational steps of the overall research framework. This research was initiated by conducting extensive literature reviews in the field of VANETs and IoV. The aim of this process was to thoroughly understand the development of the state-of-the-art vehicular network systems. Relevant information of vehicular networks and its usage in real-time traffic information systems was gathered in order to generate meaningful research problems. In the following sub-sections, each phase describes the methods, steps and procedural involved in the development of an efficient congestion control mechanism.

There are widely used network simulators for vehicular networks, namely NS2, NS3, OPNET, OMNeT++, NetSim, GloMoSim, SSFNet and GT-Nets as explained in sub-chapter 2.5.1.1. (Sakthivel & Balaram, 2021). In this research, SUMO is choosen as the traffic flow simulator while OMNeT++ was adopted as the most appropriate network simulator, considering the parameters involved. Next, performance evaluation is performed. The metrics that were used to measure the performance of the IoV network are throughput, delay and PDR. Finally, all findings are concluded in chapter 4, 5 and 6 of the thesis.

### 3.2.1 Problem Formulation

The problem analysis and formulation were initiated with an investigative idea and analysis of VANETs and existing IoV optimization. An extensive literature review on the approaches has been carried out to explore and understand its importance in vehicular networks. This gathering of information acts as a link to reveal the inadequacies of the prevailing solutions, leading to the development of a concrete research problem. Based on the thorough study conducted, it is identified that when a large number of vehicles or nodes distribute messages at high frequency during high traffic loads, the network will be easily prone towards congestion. The consequences of this situation lead to delay in transmission of the safety messages from the source node to the other nodes circulating and connected in the same network.

The network should be free from congestion in order to deliver useful and safety packets at a short and reliable time (Zhang & Lin, 2022). In chapter 2, the details about VANETs in solving the problem of network congestion were discussed and well-presented. The modification on the optimized VANETs is able to solve the network congestion problems where it able to deliver safety packets successfully with low delay. Thus, with the implementation of the optimization of the VANETs, it is suggested to increase the overall performance of the vehicular network. The proposed optimized IoV network in this research is based on bio-inspired algorithm which is PSO algorithm. The optimization is expected to increase the network performance by using the delay as the objective function of the PSO algorithm (Royyan et al., 2018). Meanwhile, the comprehensive literature review of the bio-inspired optimization algorithm is presented in Chapter 2. Once the research problems were formulated, the network simulator selection is identified.

### 3.3 Operational Design and Procedures

The previous sections presented a general overview of the operational framework. This section introduces the proposed system architecture, design and procedure. In any vehicular networks, when a large number of vehicles connected to the network emit safety alerts at a high frequency, the CCH communication channel can become rapidly congested. (Javadpour et al., 2021; Murugan et al., 2020). Due to the condition mentioned, a network need more time to load and distribute the message to the neigboring vehicles, thus lead to packet delivery delay and high waiting time (Hatim et al., 2018). In IoV network, vehicles will have difficulty maintaining a consistent connection because of the variety and rapid mobility characteristics (Latif et al., 2024; Kapassa et al., 2021; Tripathi, Ahad & Sathiyanarayanan, 2019; Kim, 2019). Due to the unusual characteristics as stated, the development of the IoV network for safety-related application is considered as an overwhelming task.

This research aims to address the aforementioned issues. As stated in section 3.2, the operational design and procedures are classified into three main phases in terms of the system architecture. The phases are the experimental setup, implementation and evaluation process. In the experimental setup, the simulation testbed was created. The IoV network was designed and developed. Two network scenarios were prepared which are the non-optimized IoV network and optimized IoV network. The non-optimized is referring to baseline scenario without congestion control and the optimized scheme is referred as the intervention of the congestion, integrated in the network using Particle Swarm Optimization (PSO) algorithm. The IoV network for both scenarios are verified using the OMNeT++ network simulator, with the aid of Veins. In line with the proposed operational framework and the defined research objectives, the following hypotheses are formulated to rigorously evaluate the effectiveness of the optimized IoV network compared to the non-optimized baseline. The hypothesis and evaluation emphasizes throughput, PDR and delay as the primary performance metrics, while transmission rate and CBR are considered as the influencing factors. The schematic overview of the proposed work is shown in Figure 3.3.

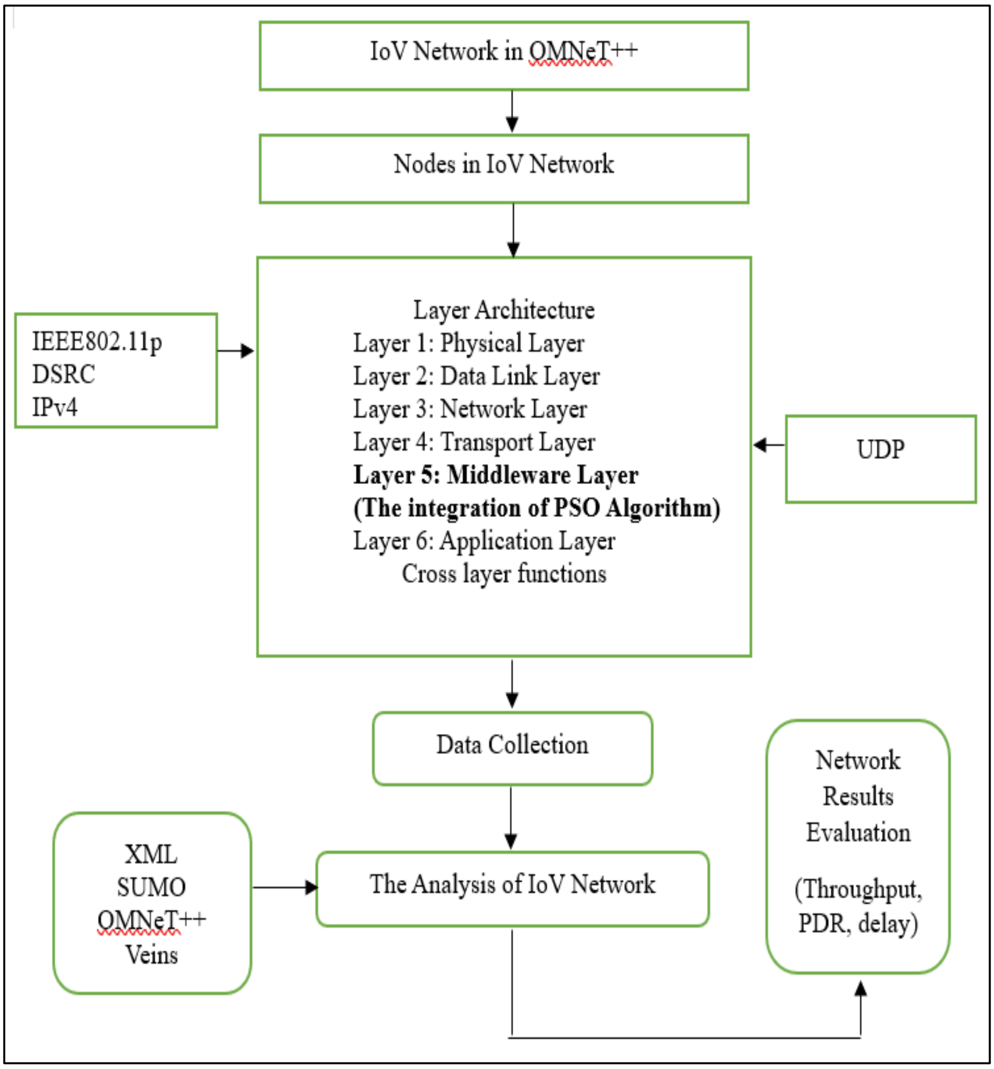



Figure 3.3 Schematic Overview of the Proposed IoV Network

Based on Figure 3.3, this research implemented the concept of seven-layered based IoV network architecture which are physical, data link, network, transport, middleware, application and security layer. Each layer plays a distinct role in ensuring reliable, low-latency dissemination of vehicular safety messages. However, the seventh layer which is the security layer is not illustrated in this study as the initial six layers are predominantly engaged, facilitating real-time, peer-to-peer communication essential for congestion avoidance. The network is extended with cross-layer optimization to support congestion control and adaptive communication.

In the physical layer (PHY), the vehicles assigned to the IoV network is equipped with embedded OBUs and sensors. It is responsible for signal transmission and reception over wireless media with the IEEE 802.11p standard. The vehicles then collect data such as speed and location, thus transmit it via CCH channel. This layer accounts for signal propagation, interference, and channel sensing. Importantly, it provides measurements of the Channel Busy Ratio (CBR), which serves as a key congestion indicator for higher-layer optimization.

The data link layer is responsible for reliable node-to-node data transfer. Medium Access Control (MAC) sublayer from IEEE 802.11p is implemented to coordinate access to the shared wireless medium to ensure time-critical safety message delivery which is the accident alert among vehicles. The layer manages packet access, retransmissions, and contention window adjustments. When multiple vehicles simultaneously compete for access, collisions and delays occur, which then lead to higher CBR values.

The network layer enables packet forwarding and routing across multiple nodes within the communication range. Since vehicular safety messages are broadcast rather than unicast, this layer ensures dissemination within the defined transmission range. A geographic broadcast strategy with suppression is employed to disseminate safety messages. Network congestion manifests as packet drops, which directly impacts the PDR.

The transport layer supports end-to-end communication control. The User Datagram Protocol (UDP) is adopted because of its lightweight nature and suitability for time-critical broadcasts. It supports connectionless, low-latency packet delivery.

The middleware layer helps in managing real-time data from multiple vehicles and ensures only relevant alerts are propagated. In other words, it coordinates interface between the application requirements and the underlying network. Traffic Control Interface (TraCI) API is implemented as a client-server interface that allows external applications to interact with a running traffic simulation. It enables the data collection of the vehicles such as position and speed of the nodes, illustrated in Figure 3.4.

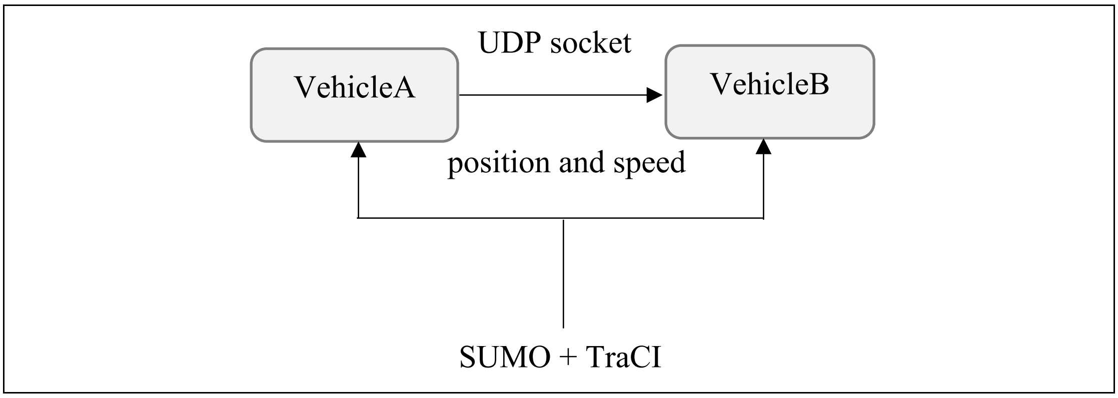



Figure 3.4 Vehicle movement using SUMO + TraCI

Figure 3.4 illustrates vehicle movement within the SUMO–TraCI simulation environment, which operates in coordination with OMNeT++ to model both mobility and communication behaviours in the IoV network. This integration establishes a closed-loop interaction where SUMO manages vehicle mobility, TraCI provides the real-time interface for data exchange and OMNeT++ simulates the network communication layer. Through this framework, real-time monitoring of key performance indicators such as throughput, PDR, and delay is enabled, alongside dynamic adaptation of communication parameters. The PSO algorithm is embedded as the optimization engine within this layer and is activated once the CBR exceeds the defined congestion threshold, ensuring efficient network performance under varying vehicular densities and traffic conditions.

The following layer in the IoV architecture is the application layer, which serves as the primary interface for safety and control functions. It generates vehicular safety messages where actions or responses are triggered upon detecting emergency events to alert nearby vehicles. These packets are broadcast at a configurable transmission rate. The application traffic load directly influences network congestion, making this layer closely linked to the optimization mechanism applied in the lower layers.

To ensure coordination among these layers, a cross-layer design is adopted to enable feedback-driven optimization across the IoV architecture. Congestion indicators measured at the PHY and MAC layers are transmitted to the middleware layer, where the PSO algorithm analyses the feedback data and dynamically adjusts transmission rates accordingly. This interaction ensures that the network can adapt to fluctuating traffic and communication conditions in real time, maintaining optimal performance and reducing congestion propagation across the network.

### 3.3.1 Simulation Setup

The simulation setup and workflow were designed to systematically evaluate the performance of the proposed optimized IoV network in comparison with the non-optimized baseline. The process ensures reproducibility, fairness and objective performance assessment. The workflow consists of scenario creation, parameter configuration, problem formulation and algorithm integration, execution, data collection and performance evaluation.

Vehicular mobility scenarios were generated using SUMO, OMNeT++ and Veins to represent realistic urban road topologies with varying vehicle densities. Vehicle movement patterns were defined to simulate dynamic traffic conditions, where nodes frequently enter and leave the communication range. Each vehicle moves at a speed between 10 to 60 km/h, simulating typical city driving conditions.

Various simulation parameters were configured to accurately reflect real-world vehicular communication scenarios. The simulated testbed for both scenarios widths a 1000x1500 meter area to ensures multi-hop communication (messages passed through intermediate nodes). Vehicular nodes randomly placed at the beginning of the simulation. Vehicles follow a random waypoint mobility pattern, which is a common choice to model dynamic and unpredictable movement behavior in vehicular networks. Each vehicle moves at a speed between 10 to 60 km/h, simulating city driving condition.

The simulation employs the IEEE 802.11p MAC protocol, specifically designed for vehicular communications, while DSRC serves as the underlying communication standard for message dissemination. Vehicles transmit packets using UDP, with a fixed data packet size of 512 bytes, reflecting typical IoV safety message payloads.

Additional communication parameters include the transmission bandwidth, set at 10 MHz, which aligns with the standard DSRC channel allocation and influences channel capacity and congestion behaviour. The transmission channel is set to Control Channel (CCH), which is commonly reserved for safety-critical message broadcasting in IEEE 802.11p/DSRC networks. The data transmission speed (PHY layer rate) is configured at 6 Mbps, which provides a balance between reliability and throughput under varying network loads. The transmission range is set at 250 meters with a transmission power of 20 dBm, providing realistic coverage and signal strength.

The duration of the simulation ranges from 50 to 250 seconds to capture network performance over time. The CBR threshold is set at 60%, based on recommendations by Patil et al. (2019), indicating that a channel is considered congested or flooded if more than 60% of its capacity is utilized. The initial transmission rate is configured at 10 Hz (10 packets per second, corresponding to a 0.1 s beacon interval), which is critical for maintaining safety and responsiveness in vehicular networks. The details are summarized in Table 3.1.

Table 3.1
Simulation Parameters

| **Parameter** | **Value** |
|---|---|
| Network range | 1000x1500m |
| Mobility model | Random waypoint |
| Data packet size | 512 bytes |
| Vehicle transmission power | 20dBm |
| Transmission range | 250m |
| MAC protocol | IEEE 802.11p |
| Communication standard | DSRC |
| Transmission bandwidth | 10MHz |
| Transmission channel | Control Channel (CCH) |
| PHY layer transmission speed | 6 Mbps |
| Vehicle Speed | 10 - 60 km/h |
| Simulation time | 50s, 100s, 150s, 200s, 250s |
| Channel busy ratio (CBR) threshold | 60% (Patil et al., 2019) |
| Initial transmission rate | 10 Hz (0.1 s beacon interval) |
| Delay | 0.1s |

Building upon the carefully configured simulation parameters, it is essential to utilize a robust and flexible network simulation environment that can accurately model the complex interactions within an IoV network. In the ever-evolving landscape of networking, the importance of such simulation tools cannot be overstated, as they play a pivotal role in testing, designing and optimizing network architectures. Network simulation enables in-depth performance evaluation and provides insights into how the network behaves under varying traffic densities, mobility patterns and communication conditions, which is crucial for validating the effectiveness of the proposed optimization mechanisms.

For this study, OMNeT++ was chosen as the primary network simulator due to its modularity, extensive vehicular network support through the Veins framework, and its ability to integrate with SUMO for realistic vehicular mobility modelling. Candidate simulators were compared in terms of modelling capability and computational complexity to ensure that the selected tool could provide both accurate and reproducible results.

The simulation scenario represents a 1000 × 1500-meter area extracted from Imagery@2023 TerraMetrics and Google Map data@2023, reflecting the real urban environment of Kuala Lumpur, Malaysia. Figure 3.5 illustrates the mapped area used in the simulations, providing a realistic geographic context for evaluating network performance under practical vehicular conditions.

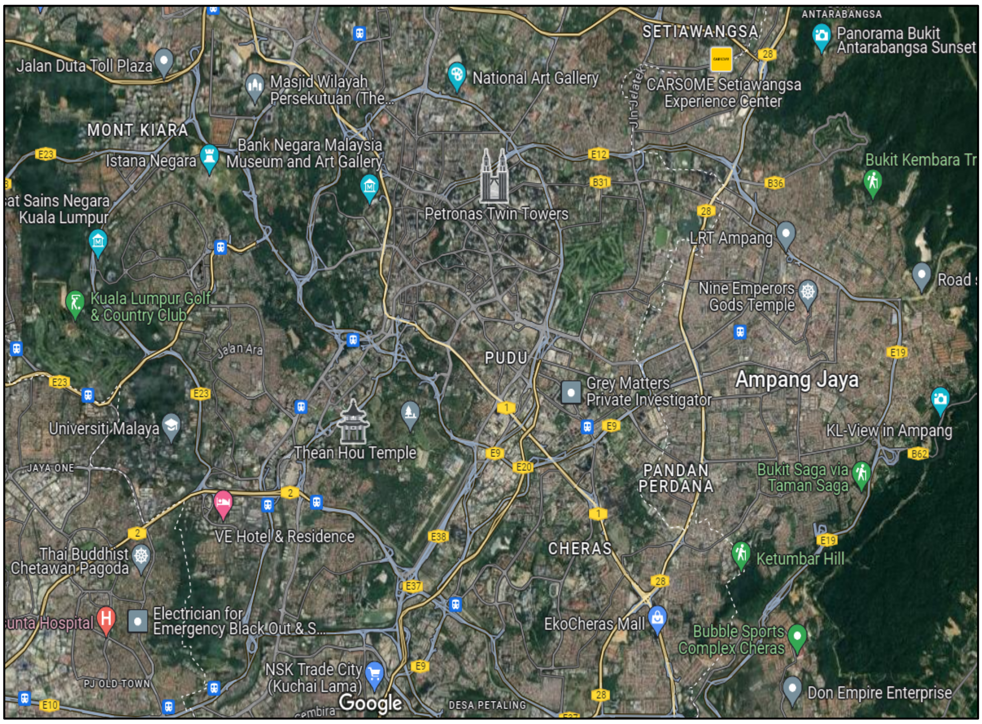



Figure 3.5 The Map of Kuala Lumpur

The experiment for traffic simulation for Figure 3.5 was conducted using Simulation of Urban Mobility SUMO 0.28.0 to test the parameters needed in detecting and forecasting traffic congestion. The SUMO simulator is an open-source microscopic, space-continuous and time discrete vehicular traffic generator package, used to generate the movements of the vehicle nodes. The movement of vehicles in the SUMO simulator is reflected in the movement of nodes in OMNeT++ network simulator. The traffic simulation of Kuala Lumpur which is intersection of Jalan P.Ramlee and Jalan Yap Kwan Seng setup was conducted through SUMO simulation. The communication range was set at the interval of 200 meters from each other up to 1000 meters range. For the wireless configuration, the IEEE 802.11p is used at the MAC layer. The focused map is illustrated in Figure 3.6.


Figure 3.6 Intersection of Jalan P. Ramlee – Jalan Yap Kwan Seng

Figure 3.6 depicts a real-world intersection in Kuala Lumpur, specifically the junction between Jalan P. Ramlee and Jalan Yap Kwan Seng, which serves as a case study for analyzing vehicular communication and traffic behavior in an urban environment. It is important to note, however, that the scenario presented is based on a simulated model rather than actual traffic data. The decision to use simulation was driven by several practical constraints, including limited access to high-resolution traffic datasets, privacy concerns related to vehicle tracking and the complexity of integrating heterogeneous real-time data sources. Simulation allows for controlled experimentation and repeatability, enabling the study of specific vehicular communication protocols and traffic patterns under predefined conditions. This approach ensures consistency in testing while avoiding the unpredictability and logistical challenges associated with collecting and processing real-world traffic data.

Figure 3.7 presents a simulation snapshot captured using SUMO. This snapshot illustrates vehicular movement in a realistic urban setting based on the road network of Kuala Lumpur. SUMO enables high-fidelity traffic simulation, where each vehicle is individually modeled with attributes such as speed, direction, acceleration and route.

During simulation, the dynamic behavior of traffic including vehicle density, intersection delays, queue formations and mobility patterns which can be observed in real-time. The simulation can be paused and resumed at any point to analyze specific traffic events or to adjust simulation parameters. The output generated by SUMO includes XML-formatted data files that record detailed information such as vehicle positions, speeds, travel times, and traffic signal states. These files are crucial for post-simulation analysis and are often used to evaluate the performance of communication algorithms, such as those for congestion control or routing in IoV networks. This level of detail allows for accurate assessment of vehicular communication strategies under realistic city traffic conditions. Figure 3.7 shows the movements of nodes in SUMO.

Figure 3.7 The Movements of Nodes During Simulation

Following the movements in Figure 3.7, the next step involves executing the simulation scenario using command-line interface. This execution phase is essential for initiating the traffic simulation and generating the corresponding output files. A snapshot of the command line execution is presented to illustrate how the simulation is configured and launched, including the use of configuration files, network definitions and route inputs. This visual representation helps clarify the procedural flow and technical setup required to simulate vehicular behavior at the selected intersection. Figure 3.8 shows the command line of the network setup.

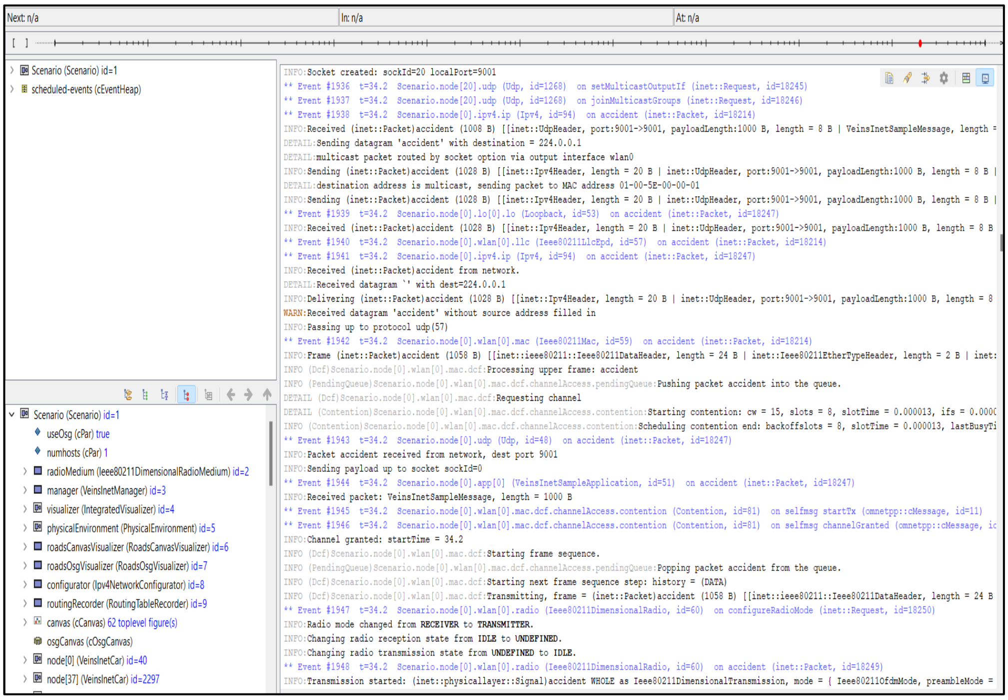


Figure 3.8 Snapshot of the Command Line Execution

Figure 3.8 shows the simulation snapshot of the command line console for execution in OMNeT++ network simulator. The raw data of the traffic are collected from the testing execution process and organized accordingly. The data then were analyzed to produce graph evaluation. The OBU-equipped vehicles detect the collision when the acceleration or gyroscopic position of the vehicle suddenly change. The broadcasting vehicle then broadcasts the information to other vehicles via V2V communication. It is important to note that in this research, the assumption of perfect physical layer performance to simplify the analysis, where any packet sent within a given radius can be perceived perfectly if not interfered by others. In addition, this study also assumes that data aggregation and analysis is performed at the cloud server level (application layer) without any interruption. Figure 3.9 is a snapshot of the execution process of the OMNeT++ network simulator.

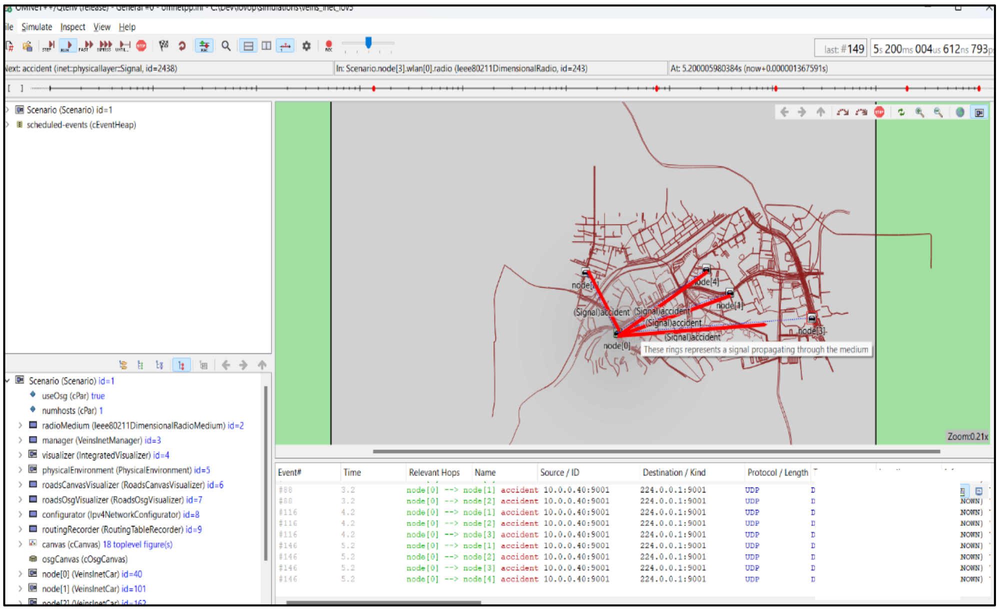


Figure 3.9 Snapshot of the Execution Process in OMNeT++

The visual in Figure 3.9 captures the interface during runtime, where modules such as network nodes, communication protocols and mobility patterns are actively simulated. The execution window typically displays real-time logs, event scheduling, and packet exchanges, which help monitor the behavior of the simulated vehicular network. This process is essential for validating the design and performance of IoV network communication strategies under controlled conditions, without relying on real-world deployment.

### 3.3.2 Mobility Design of the IoV Network

As elaborated in Chapter 2, the mobility model is a fundamental component influencing the architecture and operational efficiency of the IoV network. In this research, the initial vehicular mobility of the IoV network, as illustrated in Figure 2.2, has been modelled based on Random Waypoint (RW) mobility model which adopt Non-Homogeneous Poisson Process (NHPP) (Raja et al., 2020).

NHPP is a flexible model where it provides a powerful framework for modelling and analyzing time-dependent events in IoV network mobility, allowing for more accurate and dynamic management of vehicular networks. The intensity rate is defined as $\lambda(t)$ where, number of vehicles arriving at time $t = 0$, $N(0) = 0$. The number of vehicles, $N$ varies with time $t$ is independent. The number of vehicles arrived at time $\Delta t$ is denoted in Equation (3.1) while the probability ($P$) of number of vehicles arriving at time ($t$, $t + \Delta t$) is denoted in Equation (3.2). In addition, the probability of '$n$' vehicle arriving is denoted in Equation (3.3). The density of the network depends on the number of vehicles arrived at $\Delta t$. In NHPP, $o(\Delta t)$ is a negligible function denoted in Equation (3.4).

$$N(\Delta t) = N(t, t + \Delta t) - N(t) \tag{3.1}$$

$$P\{N(\Delta t) = 0\} = 1 - \lambda(t)\Delta t + o(\Delta t) \tag{3.2}$$

$$P\{N(\Delta t) = n\} = \begin{cases} \lambda(t)\Delta t + o(\Delta t) & if\ n = 1; \\ o(\Delta t) & if\ n \geq 2; \end{cases} \tag{3.3}$$

$$\lim_{\Delta t \to 0} \left(\frac{o(\Delta t)}{\Delta t}\right) = 0; \tag{3.4}$$

In order to validate whether the road is dense or not, the value of CBR is observed according to time $t$ is shown in Equation (3.5).

$$F2 = \int_0^t \lambda(x) \tag{3.5}$$

In the IoV network system design, the interspace between the two vehicles denoted by $Distance_t$ is calculated using the formula of Euclidean distance. It is important to mention that each vehicle has own index id, denoted as $V_{id}\,(X_i, Y_i)$; $Vn_{id}\,(X_j, Y_j)$ where $X$ and $Y$ denote the position of the vehicle. It is derived from Equation (3.6).

$$Distance = \sqrt{(X_i^2 - X_j^2) + (Y_i^2 - Y_j^2)} \tag{3.6}$$

The vehicle gives feedback when it receives the beacon message from another vehicle. The distance between two nodes (the sender and receiver) is calculated using the Broadcast Distance Factor (BDF) as in Equation (3.7).

$$\text{BDF (sender (s), receiver (r))} = \begin{cases} \frac{\text{Distance}_{\text{s-r}}}{TR_v}, & if\ Distance_t > TR_v \\ \frac{\text{Distance}_{\text{s-r}}}{D_t}, & if\ otherwise \end{cases} \tag{3.7}$$

The vehicles that equipped with OBUs detect the safety event, whenever there is a sudden change in acceleration and gyroscopic position. In terms of the message transmission, the vehicle broadcasts the message to neighbouring vehicles via V2V communication. The broadcasting vehicle is called as sender/forwarder. As mentioned previously, each vehicle in the network knows its location by using the pre-installed GPS device. The vehicle with the highest BDF is chosen as a forwarder to continue broadcasting the safety message across the network. The $TR_v$ specifies the transmission range of the vehicle and $Distance_t$ specifies the distance covered by the sender vehicle or forwarder. If the transmission range of the vehicle is less than the distance covered by that vehicle, then the vehicle sends the beacon message to all vehicles in its transmission range. This process keeps going until the transmission range of the broadcasting vehicle exceeds the distance of the travelling vehicle. In dense network, there is a higher chance of a hazardous scenario occurrence and continuous transmission of these safety messages can cause network congestion.

### 3.3.3 Design of Experiments: IoV Network Optimization based on PSO Algorithm

In the IEEE 802.11p-based IoV network, the CCH in the data link layer provides an important role in supporting time-sensitive safety applications by broadcasting event-driven and periodic beacon messages. Nevertheless, the CCH often experiences congestion due to high message traffic in dense vehicular environment, which leads to packets flooding. The detection of the congestion in the channel is observed through the level of Channel Busy Ratio (CBR). The network interface of the vehicle consistently observes the CCH states, either idle or busy. Each vehicle measures the CBR periodically by monitoring how often the communication channel is busy. It reflects the current level of channel congestion. In this study, the CBR is recorded in a 100ms interval. If the CBR value is recorded to be more than 60% (predefined threshold), the channel is considered as flooded (Sinha, 2019).

In order to overcome this problem, PSO algorithm can be effectively employed as a dynamic congestion avoidance strategy. It is a population-based optimization technique inspired by the social behavior observed in bird flocking. This bio-inspired algorithm was introduced by Kennedy and Eberhart in 1995 (Cai et al., 2020). It offers several advantages, including insensitivity to the scaling of design variables, simple implementation, ease of parallelization for concurrent processing, a derivative-free approach, minimal algorithm parameters and highly efficient global search capabilities. These parameters establish the PSO algorithm as a promising solution for diverse optimization challenges, especially within vehicular networks (Cai et al., 2020; Royyan et al., 2018). The phases of PSO algorithm is shown in Figure 3.10.

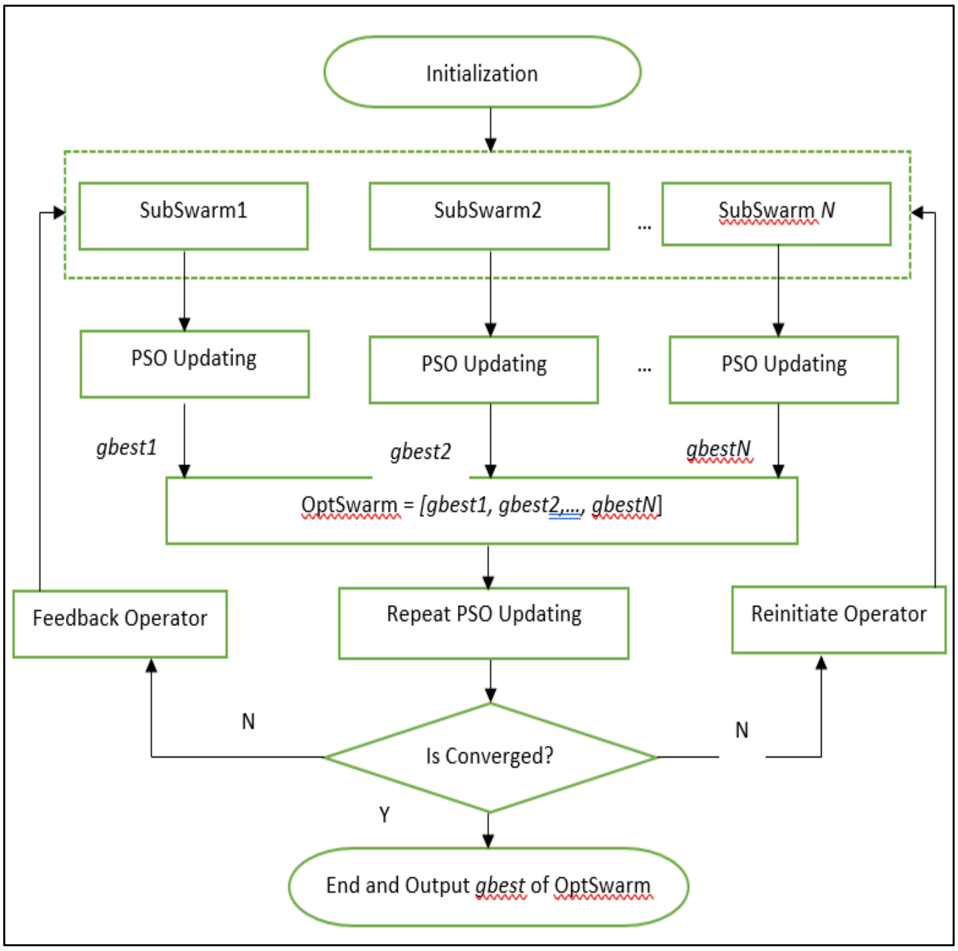



Figure 3.10 PSO Algorithm Methodology (Cai et al., 2020)

Since congestion usually occurs in any type of vehicular networks including IoV network, PSO algorithm as in Figure 3.10 is applied to optimize the transmission rate of the network with the aims to improve the throughput and minimize the delay of each node while transmitting data to neighboring nodes. PSO algorithm adjusted the data transmission rate dynamically based on the network load measured through CBR. It search for the highest transmission rate without the possibility of congestion, thereby minimizing the end-to-end latency. Figure 3.11 shows the systematic architecture of the proposed approach in this study.

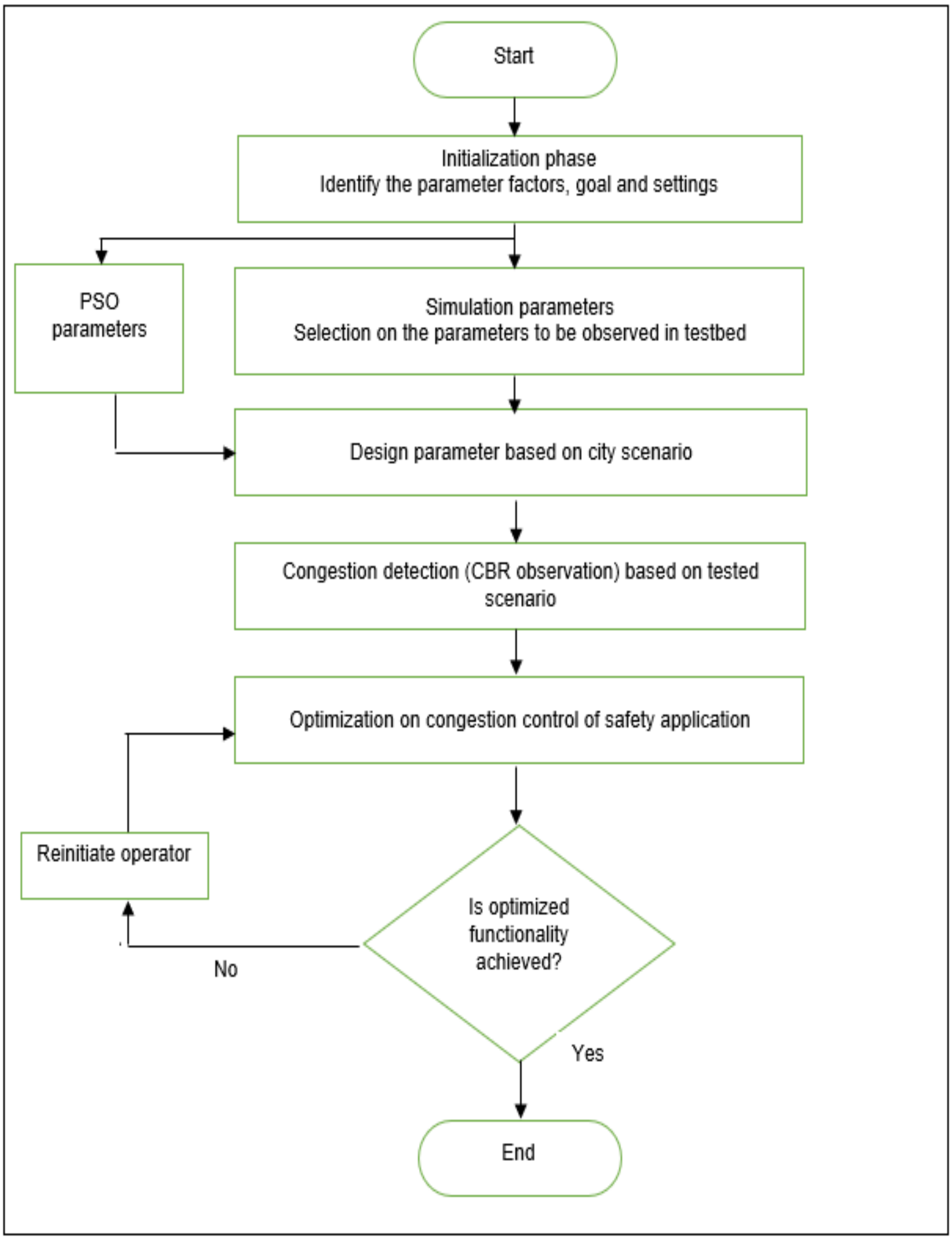



Figure 3.11 Architecture of the Proposed Optimized IoV Network

In the proposed design as shown in Figure 3.11, each vehicular node is represented as a particle in the PSO population. The position of a particle is corresponding to its current communication configuration (transmission rate), while its velocity reflects the rate at which these configurations are adapted across iterations. The PSO algorithm is designed to penalize high CBR values by reducing the fitness score for transmission parameter configurations that cause congestion of the CCH. The particles are then encouraged to search for transmission rates that reduce congestion.

Through a continuous observation of CBR starting at the physical layer and adapting transmission parameters accordingly, PSO algorithm enables a dynamic and distributed congestion control mechanism. Vehicles in congested areas will reduce their transmission rate to lower channel load, while vehicles in less busy areas may increase them to maximize communication efficiency. This balance helps maintain the overall CBR close to threshold, ensuring reliable and timely message delivery.

It is extremely important to have a balanced network parameter settings to control congestion. Several parameters were identified for the proposed work as stated in Table 3.2. The algorithm is motivated and enhanced from the previous implementation of PSO algorithm in the past applications of IoV network, VANETs and WSNs (Murugan et al., 2020; Royyan et al., 2018).

Table 3.2
PSO Algorithm Control Parameters

| **Parameter** | **Value** |
|---|---|
| Population size, i | 100 |
| Inertia weight, w | 0.7 |
| Learning factor, c1, c2 | 0.2, 0.6 |
| Number of iterations | 100 |
| Inner and Upper bound | [1,10] |
| Cognitive factor ($\alpha$) | 0.5 |
| Cognitive factor ($\beta$) | 0.4 |
| Cognitive factor ($\gamma$) | 0.1 |

Technically, the optimization is performed to optimize the transmission rate and minimize the delay of the network. The vector of position and the vector of velocity can be indicated as *Xpos = (x1, x2, x3,…, xN)* and *Velo = (v1, v2, v3,..., vN)*, respectively, where *N* is the number of particles. The personal best of each particle is denoted by *Pbest = (p1, p2, p3, ..., pN)*, whereas *Gbest* represents the global best position. The overall optimization framework for the transmission rate is summarized and shown in Table 3.3.

Table 3.3
Position, Velocity, Pbest and Gbest

| Variables | Indicators |
|---|---|
| Xpos | Current transmission rate. |
| Velo | Rate of change in the transmission rate setting. |
| Pbest | Best transmission rate value (position) found by the individual particle so far. |
| Gbest | Best transmission rate value (position) found by the any particle in the swarm. |

The inertia weight is denoted as *w* and in this case, *c1* and *c2* are two constants, referred to as the acceleration coefficients (cognitive and social), that define the weight of *Pbest* and *Gbest*, respectively. The two random numbers, *r1* and *r2*, are each generated independently using a uniform distribution in the interval [0,1]. The velocity and position of the particles are updated periodically according to following Equation in (3.8) and (3.9) (Royyan et al., 2018).

This study identified an objective function of lowering delay. Equation (3.10), *x(t)* is the objective function of each particle's fitness evaluation *f(x)*. The value of $\alpha$, $\beta$ and $\gamma$ is the weights of *F1*, *F2* and *F3* which indicates the shortest path, the smoothest path and the transmission rate of the particles respectively. *F1* represents the minimized delay or shortest route to the destination, while *F2* reflects the stability and congestion condition through CBR. The inverse of *F3* is used to balance the transmission rate as high *F3* value can overload the network and increase CBR, whereas extreme low *F3* certainly can reduce CBR but will definitely cause delay in packets delivery. The fitness function is defined as in Equation (3.11). It is a novel idea introduced for the purpose of IoV network optimization. The algorithm continues to execute until the termination criteria is met, indicated by $i < i\_max$.

$$\text{Velo}(t + 1) = w\text{Velo}(t) + c1r1(\text{Pbest} - \text{Xpos}(t)) + c2r2(\text{Gbest}(t) - \text{Xpos}(t)) \tag{3.8}$$

$$\text{Xpos}(t + 1) = \text{Xpos}(t) + \text{Velo}(t + 1) \tag{3.9}$$

$$x(t) = \alpha * F1 + \beta * F2 + \gamma * (1/ F3) \tag{3.10}$$

$$\text{Fitness function: } f(x) = 1/x(t) \tag{3.11}$$

The proposed PSO algorithm can balance the trade-off between minimizing travel distance and maintaining a smooth trajectory for the nodes by adjusting the weights. This weighted strategy allows the algorithm to find solutions that best fit the specific needs of the network, making it flexible and adaptable to the dynamic environment of the IoV network. Therefore, reducing *f(x)* is equivalent to reducing the delay.

Figure 3.12 elaborates the algorithm used in this study where *MaximIter* is denoted as the maximum number of iterations. In the algorithm, every particle needs to have a boundary in order to reduce search time. For simplicity, the lower bound is set to one whereas the upper bound is set to 10 (Cai et al., 2020; Royyan et al., 2018; Taie & Elazb, 2016).

**PSO Algorithm**

```
Randomly initialize X_i and V_i
for t to MaximIter do
    for i <- 1 to N do
        if f(x_i) < p_i then
            p_i ← f(x_i);
        else
        end
        if f(x_i) < Gbest then
            Gbest ← f(x_i);
        else
        end
        Update V with equation (7)
        Update X with equation (8)
    end
end
```

Figure 3.12 Pseudocode of the Proposed PSO Algorithm

In order to complement the pseudocode presented in Figure 3.12, Figure 3.13 illustrates the step-by-step flow of the PSO algorithm applied in this study. While the pseudocode provides a structured algorithmic representation of the procedure, the flowchart offers a visual interpretation of how particles are initialized, evaluated, and updated across iterations. It highlights the decision-making process where each particle updates its personal best (Pbest) and contributes to identifying the global best (Gbest), which guides the swarm towards the optimal transmission rate. Together, the pseudocode and flowchart provide a comprehensive view of the PSO algorithm implementation, showing both the algorithmic logic and its operational flow in mitigating congestion within the IoV network.

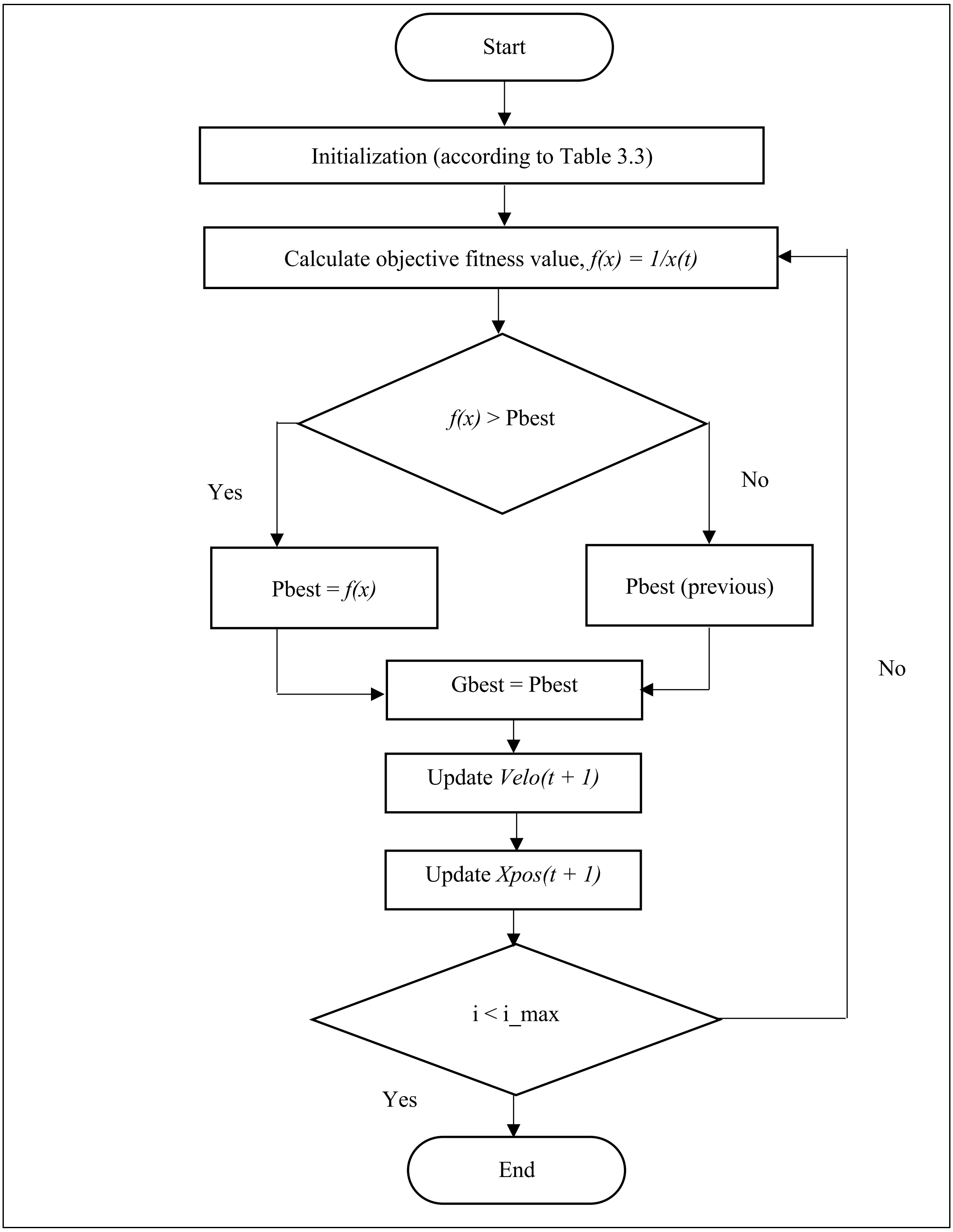



Figure 3.13 Flowchart of the Proposed PSO algorithm

In order to verify the effectiveness of the proposed approach as in Figure 3.13 in this scenario, all nodes assigned to the network have the same priority. Notably, the algorithm operates each time the number of nodes varies, allowing the algorithm changing conditions quickly and optimally. This proposed approach can significantly reduce network packet load thus minimize the packet delivery delay among the neighbouring nodes.

### 3.3.4 Data Collection

The data is collected through the network simulation as shown in Figure 3.9, which is based on network level and mobility-related parameters as in Table 3.1. This is necessary for analyzing and evaluating the non-optimized and optimized IoV network. The outputs of the network which include the throughput, PDR and delay (metrics for evaluation purpose in this study) are considered crucial indicators of network performance. The OMNeT++ with the aid of Veins, generated the logs on the node positions, movement traces, transmission range and channel utilization, consequently assisted in measuring the impact of vehicle mobility and network density.

In this study, data is generated in vector and scalar files with extension of .vec and .sca. It is further processed and evaluated via statistical tool. The Graphical User Interface (GUI) of the OMNeT++ and INET framework conributed in visualizing and providing real-time tracing of V2V interactions. The simulations were tested for two different noise parameters which are simulation time and number of vehicles. It is further illustrated in Table 3.4.

Table 3.4
Levels of Variations for Noise Parameters

| Parameter(s) | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Simulation time (seconds) | 50 | 100 | 150 | 200 | 250 |
| Number of vehicles | 15 | 30 | 45 | 60 | 75 |

The simulations involves in evaluating the peformance of the IoV network are simulation time (in seconds) and number of vehicles. There are five different parameter sets are defined, each of which represents different test parameter. As for the simulation time, it ranges from 50 seconds up to 250 seconds. The configuration values for *Simulation Time* are derived from (Mishra et al., 2023; Kaiwartya et al., 2016).

On the other hand, the initial count of vehicles starts at 15 and finished at 75 in the final set. The parameter increased by 15 vehicles in each of the consecutive scenario. As for the *Number of Vehicles*, it is obtained from (Shu & Li, 2023; Zhang et al., 2019).

The network behavior of increasing traffic density and longer intervals, is observed via the advanced experimental setup. In this study, the efficiency of the proposed optimization on the IoV network as a congestion control strategy is monitored based on the key metrics, which are the throughput, PDR and delay. The evaluation metrics are discussed in the next section.

### 3.4 Performance Evaluation

The evaluation of the proposed IoV network optimization requires special testbed setups and experiments. The simulation setups include realistic highway scenario with urban vehicular scenarios with realistic maps configuration (Royyan et al., 2018). Furthermore, the experiment involved varying parameters such as the number of vehicles, the speed of vehicles, the transmission range, the data packet size, the distance of vehicle etc. The procedures involved in the evaluation of the proposed optimized IoV network in this study are the simulation and performance analysis.

In this research, two distinct simulators, the OMNeT++ version 5.6.2 for the network simulation and the SUMO for the road traffic simulation, were constructed with the support of Veins 5.2 simulator and INET 4.5 framework. It is an open-source Inter-Vehicular Communication (IVC) simulation framework composed of an event-based network simulator and a road traffic micro simulation model (Veins, 2023). UDP socket protocol was used to establish a parallel connection between the OMNeT++ and SUMO simulators to conduct the evaluation of the communication. The Traffic Control Interface (TraCI) is the standard protocol for this kind of communication. This makes it possible to simulate network traffic and road traffic in tandem in both directions. Nodes in an OMNeT++ simulation move in sync with the movements of the vehicles in the SUMO road traffic simulator.

As mentioned earlier, the map is downloaded from the Google Maps Imagery. It is available to the public and can be access for free. It is used most to supply the digital map foundation for mapping software or a Geographic Information System (GIS). A scalable and flexible Veins simulator featuring realistic highway movement simulations was employed. A realistic mobility framework for vehicle network simulations can be created in a short duration. For critical safety and traffic information system applications, realistic highway vehicular simulations are dependent on a realistic mobility model. The data is extracted after the execution of the simulations.

### 3.4.1 Performance Metrics in IoV Network

A comprehensive performance analysis of the proposed IoV network optimization requires two distinct simulations: traffic and network. The traffic simulator generates vehicle movement patterns and mobility traces, which are then used as input for the network simulation. Meanwhile, the network simulator evaluates key performance metrics such as throughput, PDR and delay.

Several performance evaluation categories are associated with vehicular driving scenarios in the IoV environment, as identified by Termunikar (2022). Figure 3.14 illustrates the derivation of the performance analysis framework while Table 3.5 summarizes the specific metrics applied in this research.

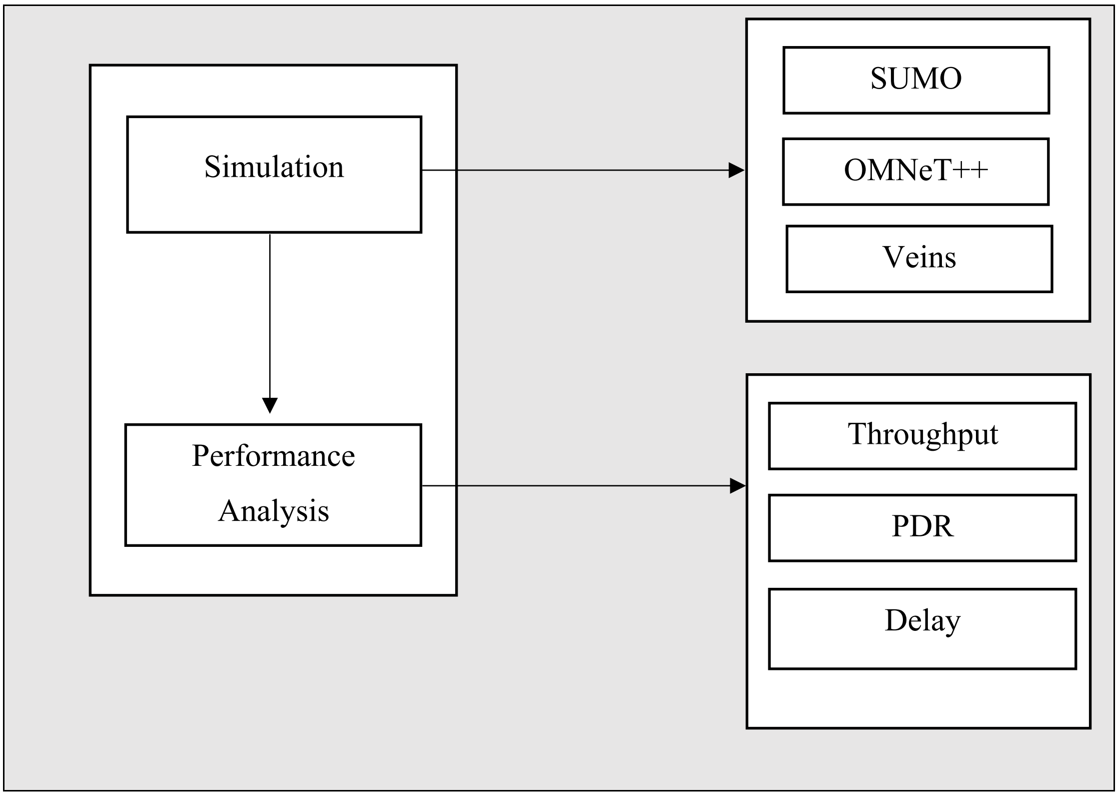



Figure 3.14 Simulation and Performance Analysis

Table 3.5
Performance Metrics

| Category | Definition |
|---|---|
| Throughput | The sum of received data frame bytes at the destinations, averaged over the total number flows in the network (Mishra et al., 2023). Throughput = $\frac{packet\ received\ in\ bits}{simulation\ time}$ |
| Packet Delivery Ratio (PDR) | The ratio between the number of received packets and the transmitted packets during the simulation time (Mishra et al., 2023). PDR = $\frac{packets\ received}{packet\ sent}$ |
| Delay | The sum of all mean delays for each vehicle, normalized over the total number of flows in the network, where mean delay is defined as the ratio between the sums of all delays and the total number of received packets (Gupta et al., 2023). Delay = $\sum(ArriveTime - SendTime)$ / Total Number of Packet |

Based on Table 3.5, the three selected QoS metrics are throughput, PDR and delay to provide a comprehensive evaluation of the performance of IoV network. Throughput measures the efficiency of the communication channel by quantifying the total amount of data successfully delivered within the simulation time. PDR evaluates the reliability of the network, as it represents the proportion of successfully received packets relative to the number of packets transmitted. This metric inherently reflects the impact of packet loss without the need for separate measurement. Delay, on the other hand, captures the timeliness of communication by measuring the average time taken for packets to reach their destination, which is particularly critical for safety-related vehicular applications. Collectively, these three parameters were selected as they represent the core pillars of QoS in vehicular networks to show efficiency, reliability and timeliness while avoiding redundancy among performance indicators.

The network optimization is formulated in order to maintain the existing protocols and other network parameters instead of engaging in costly efforts to design and implement new improved protocols. The dynamic changes of network topology in IoV network and the requirement of reliable communication among vehicles can be very costly. Improving and optimizing the network performance in the presence of any major network topology requires the system to be smart enough to cater to any changes in the road and driving condition within an error-free environment. This thesis presents an optimization of IoV network to measure throughput, delay and PDR by using PSO algorithm in order to control congestion for safety data and applications.

## 3.5 Assumptions and Hypothesis

In this simulation study, a detailed map of Kuala Lumpur Malaysia is adapted from the Google Maps database to accurately reflect the characteristics of a real-world urban vehicular environment. The chosen area includes major highways, intersections, and urban road networks, providing a realistic backdrop for evaluating vehicular communication and mobility behaviors. The vehicular traffic was modeled using the SUMO which allowed the generation of dynamic traffic flows, realistic driving behavior, and individual vehicle mobility patterns.

In order to to simulate communication between vehicles and network-related events, the OMNeT++ network simulator was employed. OMNeT++ was tightly integrated with SUMO through the Veins framework, which enables bi-directional coupling of mobility and communication modules. This integration ensured that real-time traffic conditions influenced the network behavior and vice versa, reflecting a more accurate and holistic vehicular networking environment.

Each vehicle in the simulation was explicitly modelled with a unique route, mobility trace, and communication capability, allowing for fine-grained analysis of vehicular interactions and message dissemination in the network. The entire simulation framework aimed to replicate realistic vehicular conditions in both movement and communication aspects, offering a valid testbed for performance evaluation of vehicular networking protocols and optimization algorithms. The key assumptions considered during the simulation process are outlined below:

i. Generally, a large number of vehicles transmit messages at a high regularity in the city network, which leads to network congestion.
ii. In addition, the vehicles disseminate safety messages multiple times, causing overload of packets in the network, thus increasing the possibility of packet loss.
iii. The vehicles are assumed to receive or generate more than one safety messages or packets.
iv. Data storage in IoV is unrestricted. Vehicles in the IoV network are renowned for having no power constraints and no limitation on the data storage capacity.

v. All the packets have the same priority.

On the basis of these assumptions, the following hypotheses are formulated to validate whether the PSO-based optimized IoV framework, through adaptive transmission rate control, can effectively mitigate CCH congestion and enhance network performance relative to the baseline model.

i. **Hypothesis 1 (Throughput):** The optimized IoV network achieves higher aggregate throughput than the non-optimized IoV network under equivalent transmission rates and network conditions.
ii. **Hypothesis 2 (PDR):** The optimized IoV network demonstrates a higher PDR compared to the non-optimized IoV network.
iii. **Hypothesis 3 (Delay):** The optimized IoV network results in a lower delay than the non-optimized IoV network.

## 3.6 Summary

This chapter provides an in-depth discussion of the evaluation methodology used to assess the performance of the optimized IoV network, which was developed to enhance the efficiency of safety message broadcasting in vehicular networks. The evaluation process is structured into three main phases, each addressing a critical aspect of the system design and performance validation.

The first phase focuses on identifying and analysing the fundamental challenges in vehicular network environments. This involves a comprehensive review of existing literature and prior work to establish a foundational understanding of the key issues, such as dynamic topology, high mobility and communication reliability in V2V systems.

The second phase involves the design and development of the proposed optimized IoV architecture. This includes the integration of PSO algorithm to enhance message dissemination strategies, particularly under varying network conditions. The optimization is aimed at improving the selection of forwarding nodes and reducing redundant transmissions, thereby ensuring timely and reliable message delivery.

The third phase is dedicated to the empirical evaluation of the optimized IoV scheme. Simulations are conducted to assess the system’s performance using key metrics such as throughput, PDR and delay. These metrics are analysed in relation to simulation parameters, including the number of vehicles and simulation duration, to provide a comprehensive understanding of the scalability and robustness of the proposed approach.

The subsequent chapter presents the core contribution of this research which is the optimized IoV network incorporating the PSO algorithm. It also includes a detailed performance analysis, comparing the proposed approach with existing methods to demonstrate its effectiveness in improving safety message dissemination in vehicular networks.

# CHAPTER 4
# AN OPTIMIZED INTERNET OF VEHICLES

## 4.1 Introduction

This chapter discusses on the problems of congestion in disseminating safety messages in the dense vehicular scenario. The proposed optimized IoV network is able to broadcast the safety packets with high reliability and lower delivery time to all neighboring vehicles. This chapter is organized into three main parts. Part one illustrates the overview of the proposed optimized IoV network and its design. It particularly addresses the first and second objectives in Section 1.5.

The optimized IoV network scheme design was integrated in the vehicular network to prevent congestion in the IoV network communication channel specifically in the city traffic density. Each vehicle in the network is embedded with an onboard unit (OBU) equipment, which has the same transmission power and Received Signal Strength (RSS) for all vehicles. Similar to the existing works on IoV network, there is a recurrent connectivity among nodes in the IoV network because of the high mobility of the vehicles and dynamic network topology. The vehicles were embedded with digital road maps which provide accurate locations of the roads through GPS unit and IEEE 802.11p radio equipment. The vehicles share their location in order to receive location-based services (Raja & Bashir, 2020).

The suggested optimization method in this study attempts to minimize the utilization of IoV network communication channel. The PSO algorithm was used in this research for optimizing the network. The experiments were done for each variable and parameter by using OMNeT++ simulation tool. Another experiment was run to compare the results between optimized and non-optimized IoV network. The results of the experiments are shown in the next sections.

The final part of this chapter discusses the performance evaluation of the optimized IoV network based on throughput, delay and PDR. The comparison of results of the proposed optimized IoV network with the non-optimized (original parameter settings) are also presented.

## 4.2 The Result of Data Collection

The data collection phase of this study was carried out through extensive simulation execution using OMNeT++ over a period of five months, from November 2023 to March 2024. Multiple simulation scenarios were designed to evaluate the performance of the proposed optimized under varying network conditions as mentioned in section 3.3.4. During each run, key network parameters were collected, including CBR, throughput, PDR and delay, which are critical indicators of congestion control performance in IoV network. Table 4.1 summarizes the parameters collected during the five months simulation period. These parameters were selected as they directly reflect the key performance indicators of congestion control in IoV network, namely congestion level, efficiency, reliability and latency.

Table 4.1
Summary of Collected Simulation Parameters

| Parameter | Unit | Purpose in Proposed Approach |
|---|---|---|
| Channel Busy Ratio (CBR) | % | Indicates the level of channel utilization; used to detect congestion and trigger PSO when above 60%. |
| Throughput | kbps | Evaluates network efficiency in terms of successful data delivery per unit time. |
| Packet Delivery Ratio (PDR) | % | Measures the reliability by calculating the proportion of successfully received packets over total transmitted packets. |
| Delay | ms | Reflects latency in packet transmission, which is critical for time-sensitive safety messages. |
| Transmission Rate | pkt/s | The main optimization parameter adjusted by PSO to control channel load and reduce delay under congestion. |

The simulations were executed systematically using customized code, enabling automated parameter variation and repeated trials to ensure statistical reliability. In addition to standard performance metrics such as CBR, throughput, PDR, and delay, transmission rate was explicitly included as an optimization parameter, since the PSO algorithm directly regulates it to stabilize channel utilization and improve overall network performance.

The threshold CBR value of 60% was adopted as the activation point for the PSO-based optimization mechanism. This choice is informed by previous studies on congestion control in vehicular networks (as mentioned in Chapter 3), which indicate that network performance begins to degrade noticeably when channel utilization exceeds approximately 60%, due to increased packet collisions and queuing delays. Setting the threshold at 50% would result in overly conservative optimization, potentially underutilizing the available channel capacity and reducing throughput unnecessarily. Conversely, a 70% threshold would allow excessive channel loading before intervention, increasing the risk of packet loss and high delays, which could compromise the timely delivery of safety-critical messages. Therefore, 60% represents a balanced point, where it provides sufficient headroom to accommodate normal variations in vehicle density while ensuring that the network remains responsive to congestion, minimizing delays and maximizing reliable message delivery.

During transient conditions, such as sudden increases in vehicle density, short-lived overshoots may occur. However, these are quickly stabilized as the PSO algorithm dynamically adjusts the transmission rate. Table 4.2 shows the observation of transmission rate and CBR over simulation time, highlighting the effectiveness of the 60% threshold in maintaining stable and efficient channel utilization across diverse vehicular densities and communication durations.

Table 4.2
Transmission Rate and CBR towards Simulation Time

| **Simulation Time(s)** | **Tx Rate Non-optimized (pkt/s)** | **CBR Non-optimized (%)** | **Tx Rate Optimized (pkt/s)** | **CBR Optimized (%)** |
|---|---|---|---|---|
| 50 | 29.6 | 74 | 19.6 | 56 |
| 100 | 31.2 | 78 | 21 | 60 |
| 150 | 34.4 | 86 | 21.7 | 62 |
| 200 | 35.2 | 88 | 22.05 | 63 |
| 250 | 36 | 90 | 22.4 | 64 |

In the non-optimized case, the transmission rate (Tx) increases steadily from approximately 29.6 packets per second at 50 seconds to about 36 packets per second at 250 seconds. This uncontrolled growth in transmission rate causes the CBR to rise sharply from 74% to 90%, indicating channel saturation. The reason for this trend is that as simulation time progresses, more packets accumulate in the network, and without any adaptive mechanism, vehicles continue transmitting at high rates, which results in excessive contention and collisions. In contrast, the optimized case with PSO demonstrates a more controlled behavior, where the transmission rate is regulated between 19.6 packets per second at 50 seconds and 22.4 packets per second at 250 seconds. By moderating the transmission rate, the CBR remains stable in the range of 56–64%. This is achieved because PSO algorithm detects when the CBR exceeds the threshold of 60% and dynamically reduces transmission rates, thereby keeping the channel within the safe operating region and preventing saturation.

While the variation in simulation time highlights how prolonged network activity impacts transmission rate and CBR, it is equally important to examine how changes in vehicle density influence congestion behavior under both optimized and non-optimized conditions. Table 4.3 show the transmission rate and CBR towards number of vehicles.

Table 4.3
Transmission Rate and CBR over Number of Vehicles

| Number of Vehicles | Tx Rate Non-optimized (pkt/s) | CBR Non-optimized (%) | Tx Rate Optimized (pkt/s) | CBR Optimized (%) |
|---|---|---|---|---|
| 15 | 24.8 | 62 | 18.2 | 52 |
| 30 | 29.6 | 74 | 20.65 | 59 |
| 45 | 32.8 | 82 | 21.35 | 61 |
| 60 | 35.2 | 88 | 22.05 | 63 |
| 75 | 36.8 | 92 | 23.1 | 66 |

In the non-optimized case, the transmission rate (Tx) rises from approximately 24.8 packets per second with 15 vehicles to about 36.8 packets per second when the number of vehicles increases to 75. This aggressive increase in transmission activity leads to a corresponding surge in CBR, which escalates from 62% to 92%, clearly reflecting channel saturation. The primary cause of this behavior is the uncontrolled competition among vehicles for channel access, where higher density translates directly into more collisions and longer delays. On the other hand, the optimized case with PSO algorithm shows a more adaptive pattern, moderating transmission rates between 18.2 packets per second at 15 vehicles and 23.1 packets per second at 75 vehicles. By dynamically adjusting the transmission rate in proportion to vehicle density, the PSO mechanism maintains the CBR within a safer range of 52–66%. This adaptive control prevents saturation, ensures fairer access to the medium, and sustains network performance even under heavy traffic conditions.

The results from both simulation time and vehicle density scenarios collectively demonstrate the effectiveness of the proposed PSO-based optimization. By adaptively regulating transmission rates whenever the CBR exceeds 60%, the system consistently prevents channel saturation, stabilizes CBR within the safe region and achieves higher fitness values compared to the baseline. This confirms that dynamic adjustment of transmission rate is the key mechanism through which the proposed approach improves congestion control performance in IoV networks. This controlled behavior accounts for the observed improvements in throughput, PDR and delay performance. These improvements were further validated through benchmarking, which was conducted using two approaches. First, the performance was compared against a baseline IoV network without optimization, which represents the conventional configuration of beaconing and transmission parameters. This provided a direct measure of improvement achieved through the optimized scheme. Second, the results were aligned with performance ranges reported in prior studies, including clustering-based methods (Khan et al., 2018; Aadil et al., 2018; Rawat et al., 2017) and resource allocation approaches (Lin & Zhang, 2022; Zhang et al., 2022). These studies serve as recognized benchmarks for congestion control in IoV networks. Using throughput, PDR and delay as standard QoS metrics, the findings confirmed that the proposed framework not only falls within expected ranges of prior work but also demonstrates superior performance in terms of faster convergence, higher reliability and reduced delay. With the benchmarking approach established, the next section presents the simulation results, comparing the performance of the optimized PSO-based IoV network with the non-optimized baseline, beginning with variations in simulation time.

## 4.3 Simulation Results of Optimized vs Non-optimized IoV Network based on Simulation Time

This section provides a detailed discussion on the simulation results, the throughput, PDR and delay obtained for optimized and non-optimized IoV network in different simulation time. Figure 4.1, 4.2 and 4.3 below illustrates the performance of the optimized over non-optimized network.

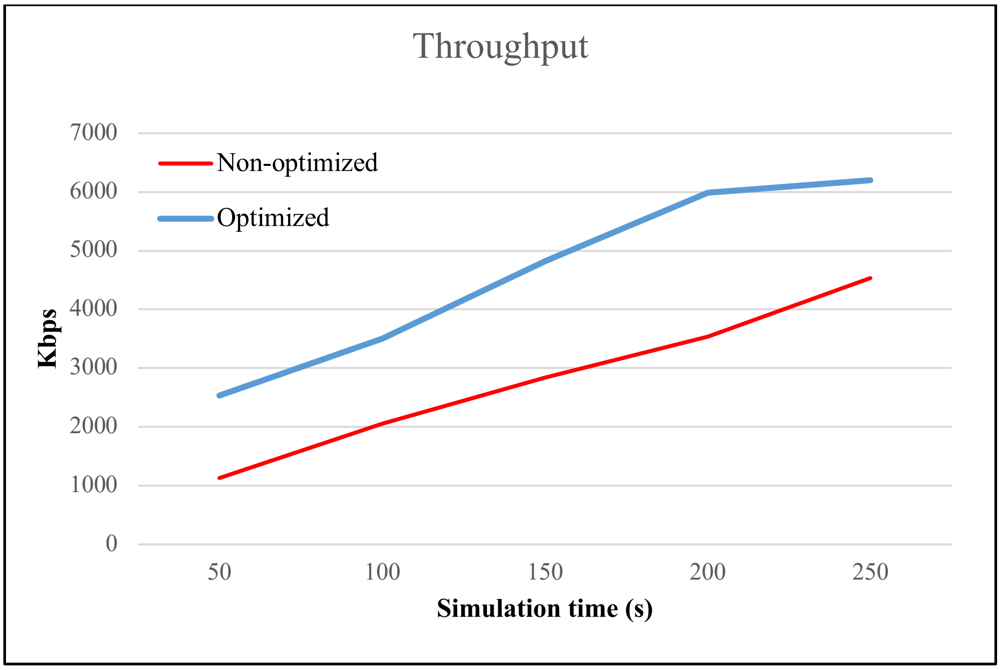



Figure 4.1 Performance of Throughput for Optimized and Non-optimized Network

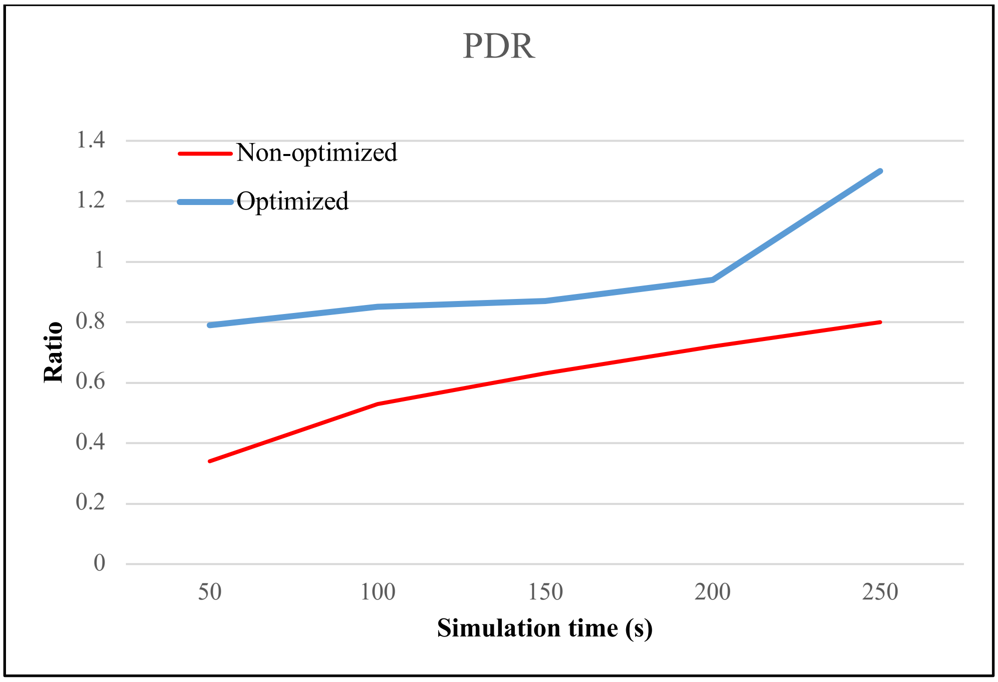



Figure 4.2 Performance of PDR for Optimized and Non-optimized Network

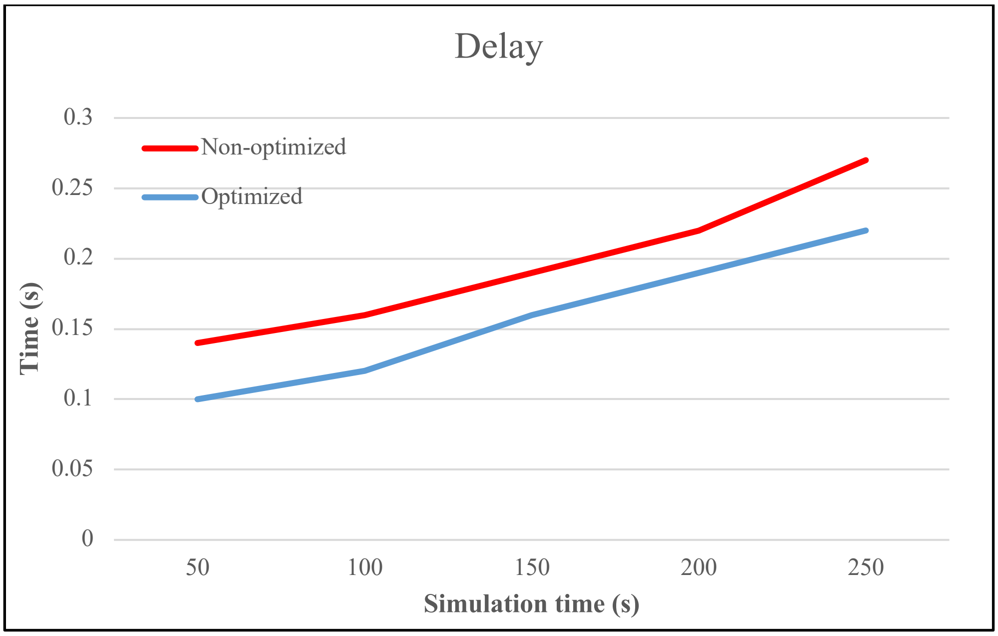



Figure 4.3 Performance of Delay for Optimized and Non-optimized Network

Figures 4.1, 4.2, and 4.3 present the evaluation of the proposed optimized IoV network compared with the non-optimized baseline across different simulation times: 50 s, 100 s, 150 s, 200 s, and 250 s. The primary objective of this experiment is to assess the impact of the proposed optimization mechanism under varying packet transmission densities and to determine how network performance evolves over time. In all figures, the blue line represents the optimized IoV network, while the red line corresponds to the non-optimized parameters.

Figure 4.1 illustrates the throughput performance of both networks. It is evident that the optimized IoV network consistently achieves higher throughput across all simulation durations. This improvement, averaging 23%, demonstrates that the PSO-based transmission rate adjustment effectively reduces channel congestion, allowing more packets to be successfully delivered per unit time. The upward trend of the blue line indicates that as the network adapts to higher traffic densities, the optimization mechanism maintains efficient channel utilization, preventing throughput degradation that is observed in the non-optimized network.

Figure 4.2 shows the PDR for both networks. The optimized network achieves an average improvement of 37%, reflecting a higher reliability in message delivery. The gap between the optimized and non-optimized lines highlights the impact of congestion control: by dynamically adjusting the transmission rate when the CBR exceeds the 60% threshold, the optimized network reduces packet collisions and loss, ensuring that safety-critical messages reach their intended recipients. This is particularly important in dense vehicular environments, where message loss could compromise real-time communication and safety applications.

Figure 4.3 depicts the performance of the delay. The optimized network exhibits an average reduction of 12% in delay compared to the baseline. This indicates that the proposed method not only improves throughput and reliability but also enhances the timeliness of message delivery, which is a critical requirement for safety applications in IoV networks. The smaller and more stable delay curve of the optimized network demonstrates the PSO algorithm's ability to stabilize channel utilization under fluctuating traffic conditions, preventing sudden spikes in latency that occur in the non-optimized network.

Finally, Figure 4.4 presents a comprehensive view of the overall network performance over simulation time, aggregating improvements in throughput, PDR, and delay. The consistently superior performance of the optimized network underscores the effectiveness of the proposed congestion control mechanism, particularly in dynamically changing vehicular scenarios. Collectively, these results validate that the optimized IoV network not only mitigates congestion but also enhances communication reliability, efficiency, and responsiveness, addressing the key objectives of this study.

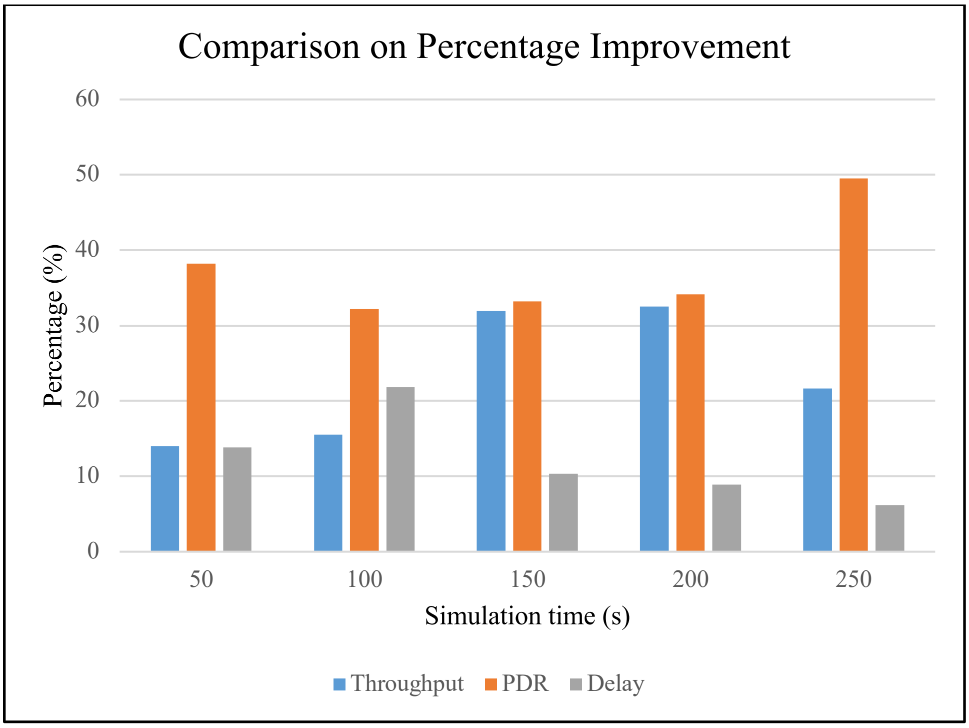



Figure 4.4 Comparison of Percentage Values based on Simulation Time

Table 4.4
Percentage Improvement based on Simulation Time

| Simulation Time(s) | 50 | 100 | 150 | 200 | 250 | Average |
|---|---|---|---|---|---|---|
| Throughput | 14.04 | 15.54 | 31.94 | 32.49 | 21.66 | **23.13** |
| PDR | 38.18 | 32.2 | 33.24 | 34.13 | 49.53 | **37.46** |
| Delay | 13.85 | 21.82 | 10.31 | 8.92 | 6.19 | **12.22** |

Based on Table 4.4, the PDR in the proposed approach increased significantly from 38.18% at 50 s to 49.53% at 250 s, while throughput showed an average improvement of 23.13%. The improvement in delay was more moderate, averaging 12.22%, yet the proposed approach consistently outperformed the non-optimized baseline across all simulation times. These numerical results provide a clear summary of the trends already illustrated in Figures 4.1 to Figure 4.4, confirming the consistent performance advantages of the optimized network.

This improvement reflects the ability of the network to adapt to temporal variations, such as vehicles entering or leaving communication range, transient congestion events, and fluctuating traffic patterns. As discussed in Chapter 2, delay, PDR and throughput are critical for safety message dissemination in IoV networks. Higher throughput allows more messages to be transmitted successfully, improved PDR ensures reliable delivery, and reduced delay guarantees messages reach their destination within the tight time constraints required for real-time vehicular safety applications, including collision avoidance and emergency braking.

The PSO-based optimization mechanism enables this performance by dynamically adjusting the transmission rate whenever the CBR exceeds the 60% threshold, stabilizing channel load under fluctuating conditions. Therefore, the improvements summarized in Table 4.4 confirm that the proposed network sustains reliable, timely and efficient communication over time, addressing the challenges identified in Chapter 2 regarding dynamic network behaviour in dense IoV environments.

## 4.4 Simulation Results of Optimized vs Non-optimized IoV Network based on Number of Vehicles

This section provides a brief discussion on the simulation results the throughput, PDR and delay obtained for optimized and non-optimized IoV network for different number of vehicles. Figure 4.5, 4.6 and 4.7 below illustrates the performance of the optimized over non-optimized network

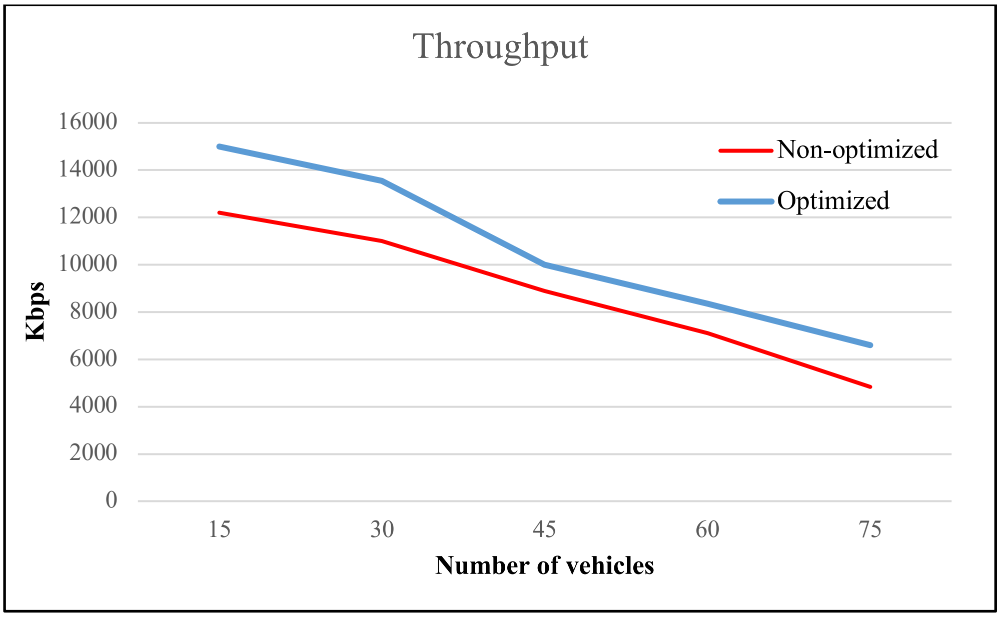



Figure 4.5 Performance of Throughput for Optimized and Non-optimized Network

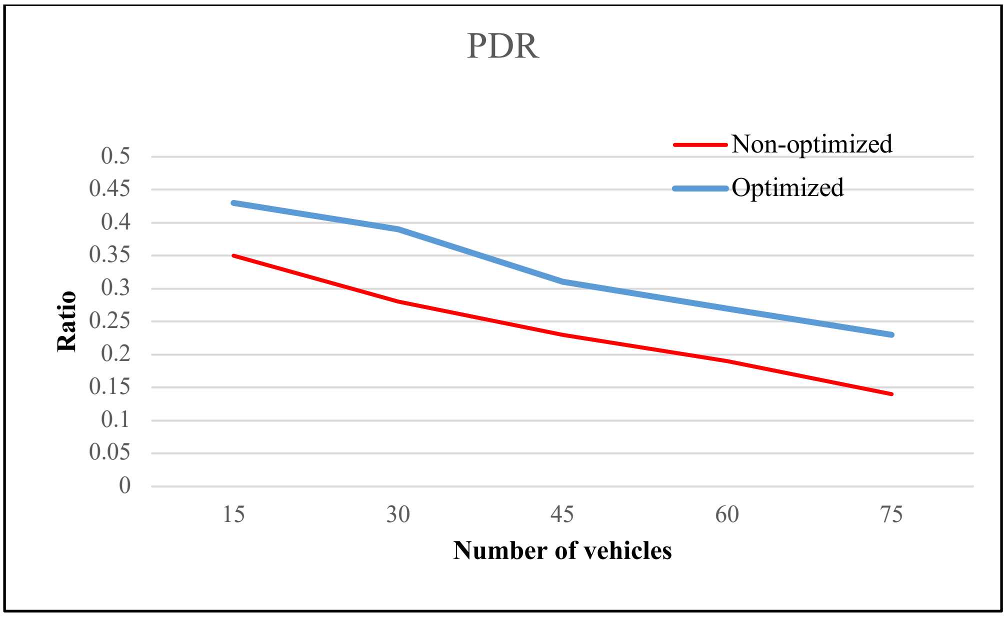



Figure 4.6 Performance of PDR for Optimized and Non-optimized Network

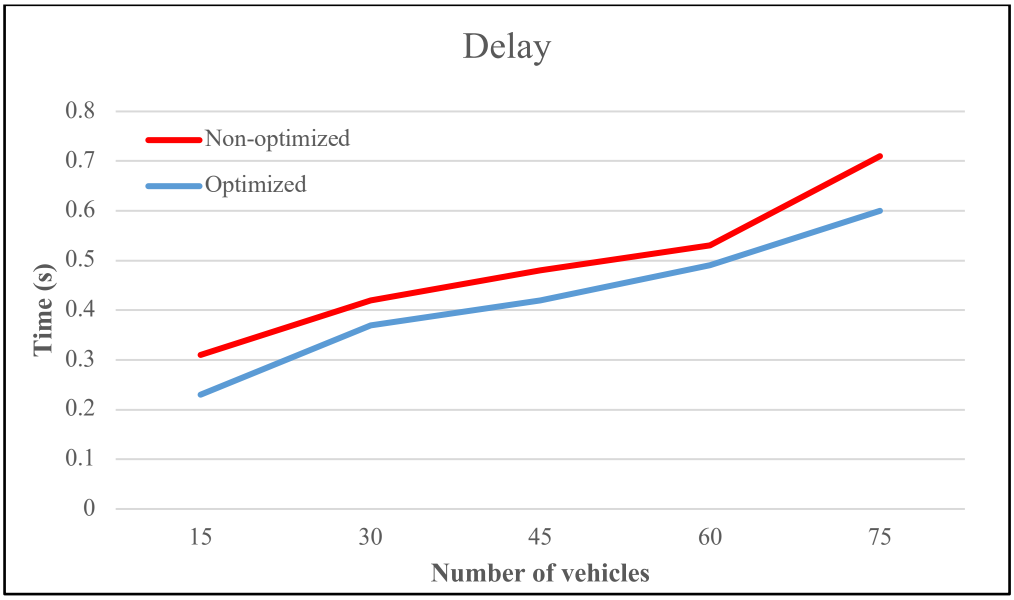



Figure 4.7 Performance of Delay for Optimized and Non-optimized Network

Figures 4.5, 4.6 and 4.7 illustrate the evaluation of the proposed optimized IoV network compared with the non-optimized baseline across different numbers of vehicles: 15, 30, 45, 60, and 75. The objective of this experiment is to assess the performance of the optimization scheme under varying vehicular densities, which directly impact channel congestion and packet transmission efficiency. In all figures, the blue line represents the optimized IoV network for safety packets, while the red line corresponds to the non-optimized scheme.

Figure 4.5 shows the end-to-end delay performance. As the number of vehicles increases, the non-optimized network exhibits a noticeable rise in delay due to higher channel contention and packet collisions. In contrast, the optimized network maintains a lower and more stable delay, with an average improvement of 15.3%. This demonstrates that the PSO-based transmission rate adjustment effectively mitigates congestion even as vehicle density rises, ensuring that safety-critical messages are delivered promptly.

Figure 4.6 presents the PDR. The optimized network consistently achieves a higher PDR across all vehicle densities, with an average improvement of 15.1% over the baseline. This indicates that the proposed optimization reduces packet loss caused by collisions and channel saturation, which is particularly important in dense traffic scenarios where reliable message dissemination is crucial for vehicle safety and cooperative driving.

Figure 4.7 depicts the throughput performance. Similar to PDR, the optimized network shows a clear advantage, achieving an average throughput improvement of 13.91%. This improvement reflects the ability of the network to handle a higher volume of packet transmissions efficiently, even as the number of vehicles increases, by dynamically adjusting the transmission rate and maintaining the channel busy ratio below the 60% threshold.

Finally, Figure 4.8 provides a consolidated view of overall network performance across different vehicle densities, highlighting that the proposed optimization scheme consistently outperforms the non-optimized baseline in terms of delay, PDR and throughput. Collectively, these results confirm that the optimized IoV network is robust against increased vehicular density, maintaining reliable, timely, and efficient communication. This is crucial for real-world urban traffic scenarios, where vehicle numbers fluctuate dynamically and maintaining safe, low-latency communication is essential for collision avoidance, emergency alerts, and cooperative driving systems.

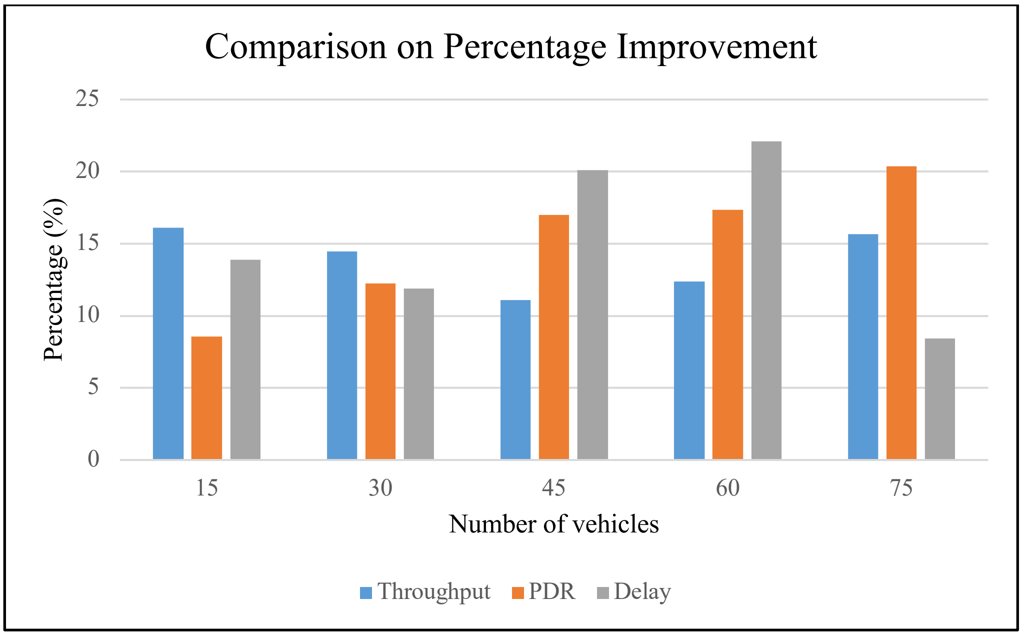



Figure 4.8 Comparison of Percentage Values based on Number of Vehicles

Table 4.5
Percentage Improvement based on Number of Vehicles

| **Number of Vehicles** | **15** | **30** | **45** | **60** | **75** | **Average** |
|---|---|---|---|---|---|---|
| Throughput | 16.13 | 14.45 | 11.09 | 12.37 | 15.65 | **13.91** |
| PDR | 8.54 | 12.23 | 17.01 | 17.34 | 20.39 | **15.1** |
| Delay | 13.89 | 11.88 | 20.12 | 22.11 | 8.44 | **15.3** |

Based on Table 4.5, the delay in the proposed optimized IoV network decreased slightly from approximately 2% at 15 vehicles to 8.44% at 75 vehicles, while PDR and throughput showed more substantial improvements, with averages of 15.1% and 13.91%, respectively. These results indicate that as vehicular density increases, the network experiences higher congestion in the non-optimized scenario, leading to increased delays and packet loss. In contrast, the optimized network maintains stable performance, demonstrating the effectiveness of the proposed approach in handling varying traffic densities.

The observed trends confirm that the number of vehicles is a key factor influencing network performance, as higher vehicle density increases channel contention and the likelihood of packet collisions. Despite these challenges, the proposed PSO-based optimization scheme dynamically adjusts the transmission rate whenever the CBR exceeds the 60% threshold, mitigating congestion and maintaining consistent delay, PDR and throughput performance.

From a practical perspective, these improvements are critical for real-world IoV applications. In dense urban environments, the timely and reliable delivery of safety messages is essential for collision avoidance, cooperative driving and emergency alerts. The proposed optimized network ensures that even as vehicle numbers increase, the network can scale efficiently, providing reliable communication and reducing latency for safety-critical messages, which aligns with the challenges and recommendations discussed in Chapter 2 regarding vehicular density and congestion management.

## 4.5 Summary

This study introduces an optimized IoV network architecture designed to function as a congestion control mechanism, aiming to mitigate or prevent network congestion. In high-density vehicular environments, a substantial volume of packets is generated and transmitted at high frequencies, often with repeated broadcasts. Concurrently, numerous vehicles disseminate safety-based messages at similarly elevated transmission rates. This high communication load contributes to channel congestion, which degrades the performance of safety message dissemination. Extensive simulation experiments were conducted to evaluate the effectiveness of the proposed architecture using realistic vehicular mobility and communication models. The results demonstrate that the optimized IoV framework consistently outperforms the baseline non-optimized architecture across several key performance metrics. Notably, significant improvements were observed in terms of overall network throughput, reduction in transmission delay and enhancement of the PDR. These findings confirm the potential of the proposed solution to enhance the reliability and efficiency of vehicular communications in congested network conditions.

# CHAPTER 5
# PSO ALGORITHM AS THE OPTIMIZATION METHOD

## 5.1 Introduction

This chapter aims to address the problem with the current IoV network. IoV network architecture relies heavily on efficient communication between vehicles (V2V) and between vehicles and objects (V2X) to ensure safety, traffic management, and data sharing. However, the dynamic and decentralized nature of the IoV architecture presents significant challenges, including high mobility, varying network topologies, and real-time data processing requirements. In this thesis, the optimization of IoV network using PSO algorithm is introduced as a congestion control mechanism to improve the performance of the IoV network. As per discussion in Chapter 2, PSO algorithm is increasingly recognized as a powerful optimization method for the IoV network, addressing the complex challenges of vehicular networks. One of the key advantages of adapting PSO algorithm in IoV applications is bacause of its ability to quickly converge to high-quality solutions with relatively low computational complexity. This makes it particularly suitable for the real-time and distributed nature of vehicular networks, where rapid decision-making is crucial. Additionally, the flexibility of PSO algorithm allows it to adapt to changing network conditions and topology, making it robust against the inherent uncertainties and variations in IoV environments.

Optimizing crucial network parameters specifically the transmission rate, plays a vital role in enhancing the performance of the IoV network. The proposed PSO algorithm addresses this need by effectively reducing channel congestion, which in turn leads to improved throughput, lower delay, higher PDR and greater overall reliability of vehicular communication. This chapter outlines the contribution of the proposed approach, emphasizing its impact on optimizing IoV network performance under dynamic traffic conditions.

## 5.2 The Proposed PSO Algorithm

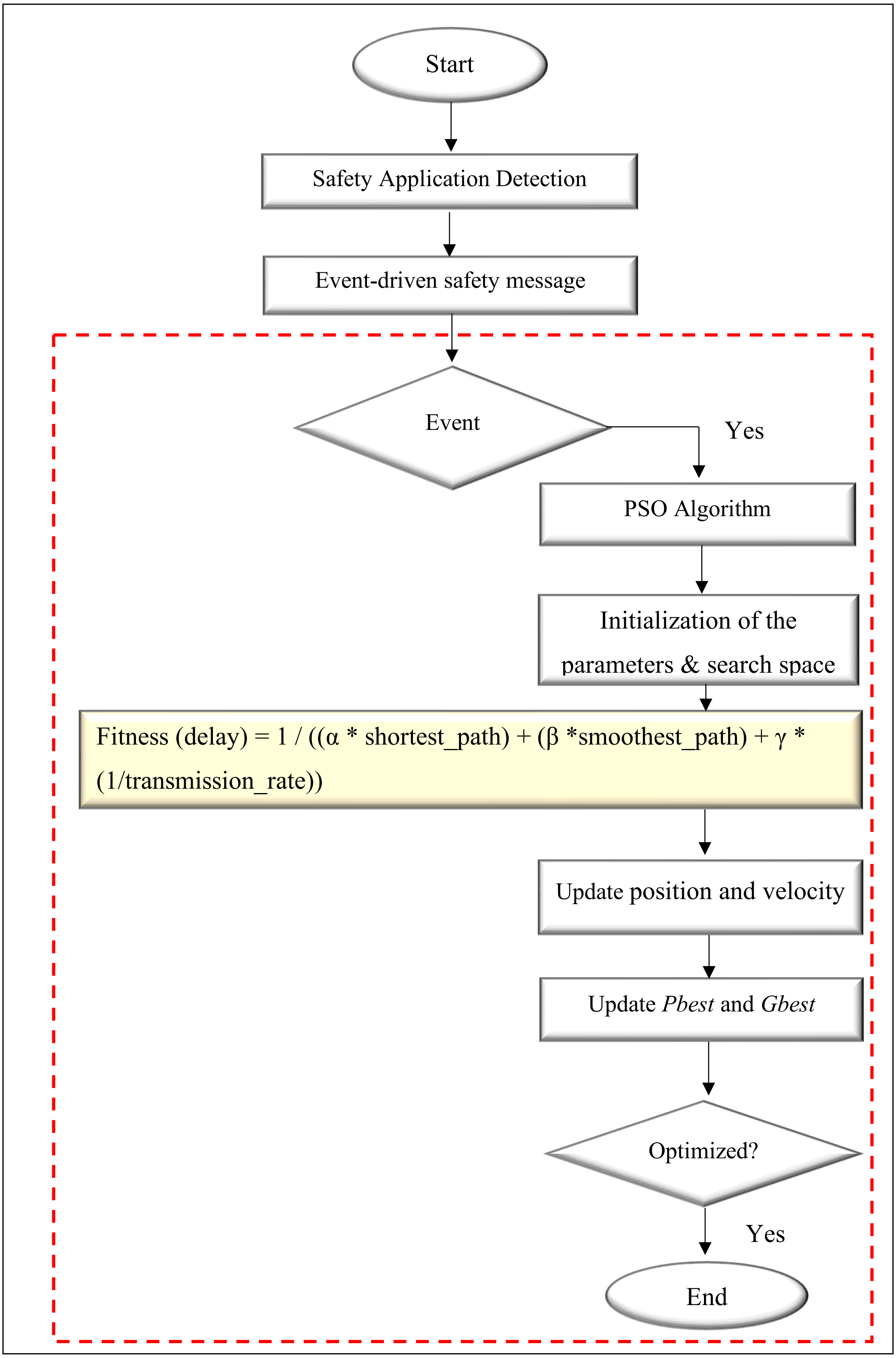
In recent years, numerous researchers have applied optimization algorithms in IoV network, particularly for improving clustering techniques to enable more efficient and reliable data transmission (Khan et al., 2018). These approaches often focus on forming optimal network structures to enhance communication performance. However, many of these studies have not adequately addressed the issue of network congestion caused by event-driven safety message dissemination, which is critical for real-time vehicular applications.

To tackle this challenge, the proposed PSO algorithm presented in this research is specifically tailored for optimizing the dissemination of safety packets within an IoV environment. Unlike conventional methods that focus purely on clustering, this approach aims to reduce channel congestion and enhance the timely delivery of safety-critical information by dynamically optimizing network parameters based on current traffic and communication conditions.

The algorithm leverages the swarm intelligence behavior of PSO, where a group of candidate solutions (particles) explore the solution space and iteratively converge towards the optimal strategy for data dissemination. Each particle evaluates possible dissemination paths or priorities, adjusting its position based on individual experience and the collective intelligence of the swarm.

As illustrated in Figure 5.1, the flowchart outlines the major steps involved in the optimization process which starts from initialization of the swarm, fitness evaluation, iterative updates of particle positions and velocities until convergence criteria are met. The output is an optimized transmission strategy that minimizes congestion and ensures the efficient delivery of event-driven safety messages in the IoV network.

This PSO-based approach provides a promising solution to the scalability and congestion issues in dense IoV environments, making it highly relevant for real-time applications in smart transportation systems.




- - - - - Contribution of the Research

Figure 5.1 Flowchart of the Proposed PSO algorithm

The objective function in PSO algorithm is the criterion that the algorithm uses to evaluate and guide the particles toward the optimal solution. It is the core of the optimization process, determining the direction in which particles should move and ultimately what the best solution is. The movement of particles is illustarted in Figure 5.2.

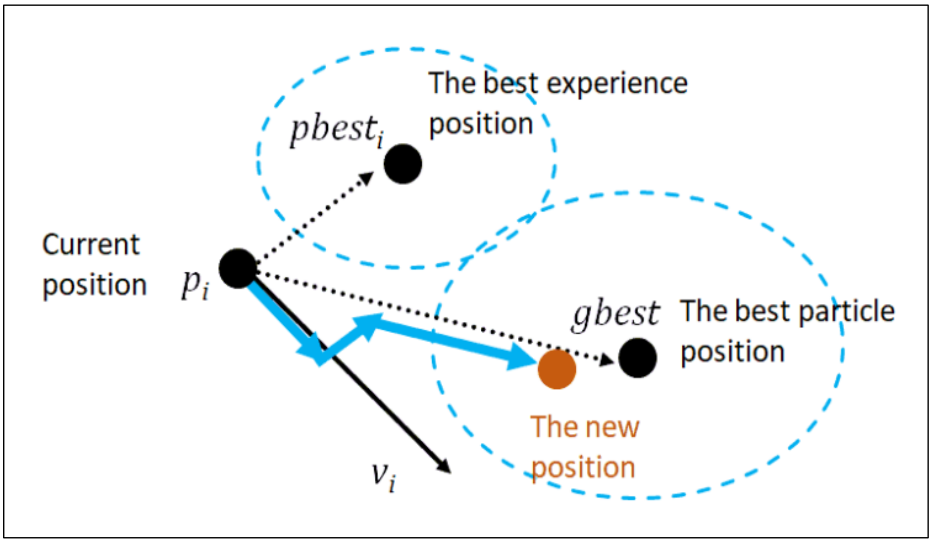



Figure 5.2 The Movement of Particles in The Search Space (Royyan et al., 2018)

In this research, the shortest and the smoothest path for the particles is strongly considered in the objective function. The objective function chosen is elaborated in detail as in sub-chapter 3.3.3. The fitness value guides the movement of the particle through the solution space. Particles move toward regions of the solution space that offer better fitness values, thereby improving the transmission rate over time.

The proposed PSO algorithm adjusted the transmission rate dynamically based on network conditions. It penalizes low transmission rates, thus avoid setting them too low. When CBR exceeded 60%, the algorithm lowers the transmission rate, preventing channel saturation.

## 5.3 Convergence Rate of Optimized IoV Network based on Simulation Time

This section provides a thorough discussion on the convergence diagram of the simulation results obtained for optimized IoV network in different simulation time.

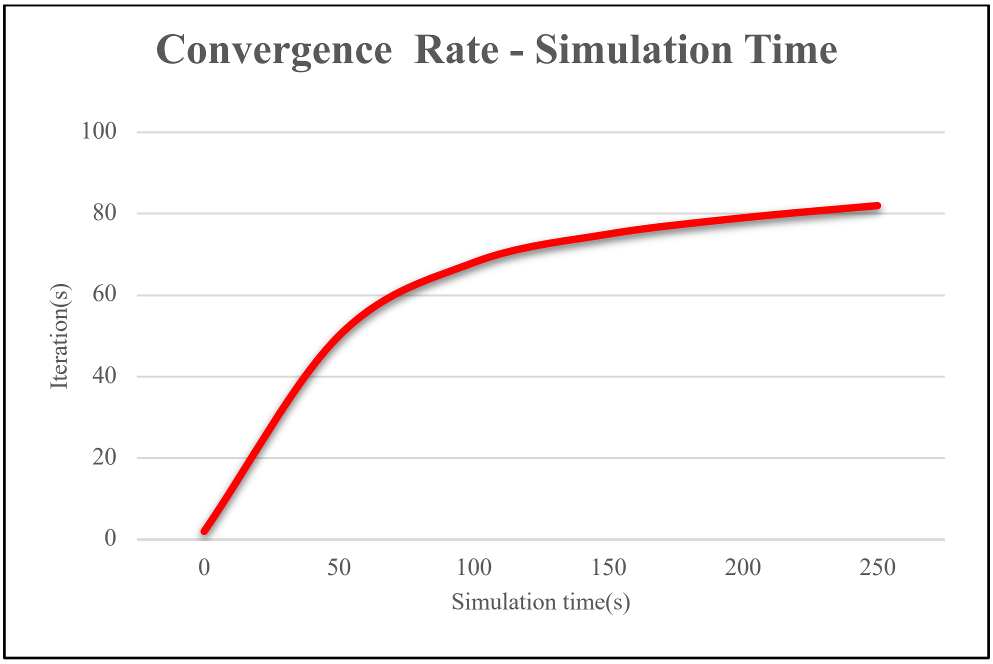



Figure 5.3 Convergence Rate based on Simulation Time

Figure 5.3 displays the relationship between convergence rate and simulation time. The X-axis represents the simulation time in seconds, and the Y-axis represents the iteration count, which indicates the number of iterations required to reach convergence. There is a clear positive correlation between simulation time and the number of iterations. As the simulation time increases, the number of iterations required for convergence also increases. The growth appears to be non-linear, especially noticeable as the simulation time increases. The graph starts with a steep slope, indicating that the system converges quickly in the initial phase of the simulation. As the simulation progresses, each subsequent iteration contributes less to convergence, indicating that the search solution is stabilizing. It can be concluded that the network becomes more complex or as the network evolves over a longer time, it requires more iterations to converge to a solution. This could be due to increasing computational complexity or more intricate dynamics at longer simulation times.

In terms of the QoS performance, the throughput and PDR are likely improve rapidly in the early phase of the simulation, similar to the steep increase in the convergence rate. As the network stabilizes which is indicated by the flattening of the curve, these metrics may also stabilize. On the other hand, the delay might start high but decreases as the convergence rate slows down, indicating that the network has optimized its paths and reduced delivery time.

## 5.4 Convergence Rate of Optimized IoV Network based on Number of Vehicles

This section provides a brief discussion on the on the convergence diagram of the simulation results obtained for optimized IoV network for different number of vehicles.

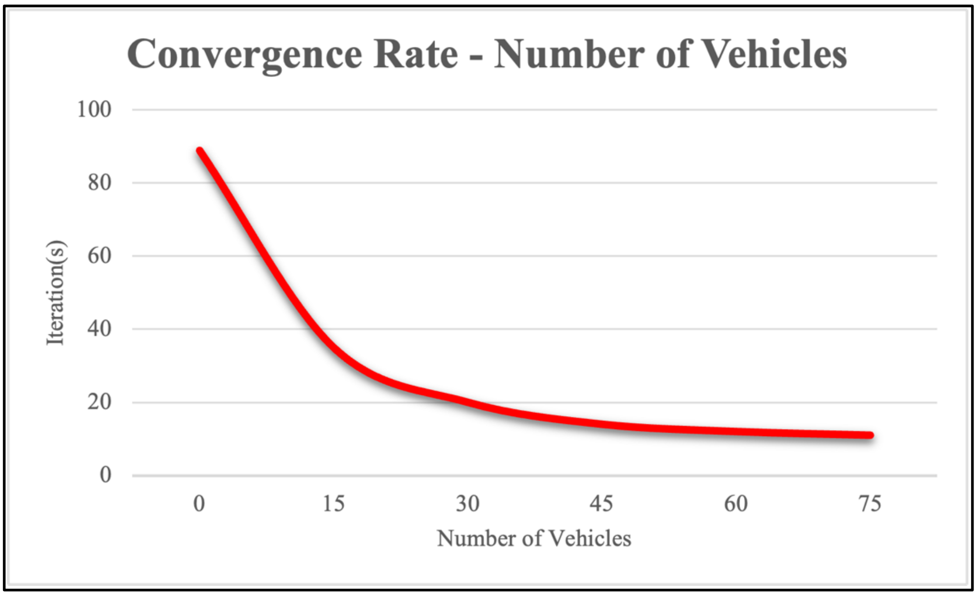



Figure 5.4 Convergence Rate based on Number of Vehicles

Figure 5.4 shows the relationship between the number of vehicles and the number of iterations required for convergence. The X-axis represents the number of vehicles, and the Y-axis represents the iteration count. It can be obeserved that when the number of vehicles is small, the convergence rate is high, meaning that it takes a longer time to converge. Later, as the number of vehicles increases the convergence time decreases rapidly, indicating that the network becomes more efficient as more vehicles are added to the IoV network. After about 45 vehicles circulated in the network, the convergence rate stabilizes. This situation indicates that adding more vehicles does not significantly reduce the time.

In other words, Figure 5.4 suggests that as the number of vehicles increases, the network becomes more efficient, reducing the time required for convergence thus obtain for better throughput, packet delivery ratio and reduced delay. Furthermore, throughput and PDR are identified as likely to increase as the network stabilizes faster with more vehicles, up to the point where the network saturation occurs. Delay is expected to decrease with the improved convergence rate as the network stabilizes more quickly, but like throughput and PDR, it might reach a minimum threshold beyond which further improvements are minimal.

In a practical scenario, managing the adjustments between these three metrics is extremely important. Adding more vehicles can enhance network performance to a point, but issues such as congestion or interference might prevent further improvements or even degrade performance. Thus, it is very important to select a suitable parameters as shown in section 3.3.3. The graph highlights the importance of finding the optimal number of vehicles for a balanced network performance.

## 5.5 PSO Algorithm Convergence Curve based on Simulation Time

In terms of the PSO algorithm convergence curve based on the simulation time, as the algorithm converges toward an ideal solution, it replicates how the fitness value increases over a hundred iterations. Figure 5.5 below shows the PSO convergence curve for simulation time.

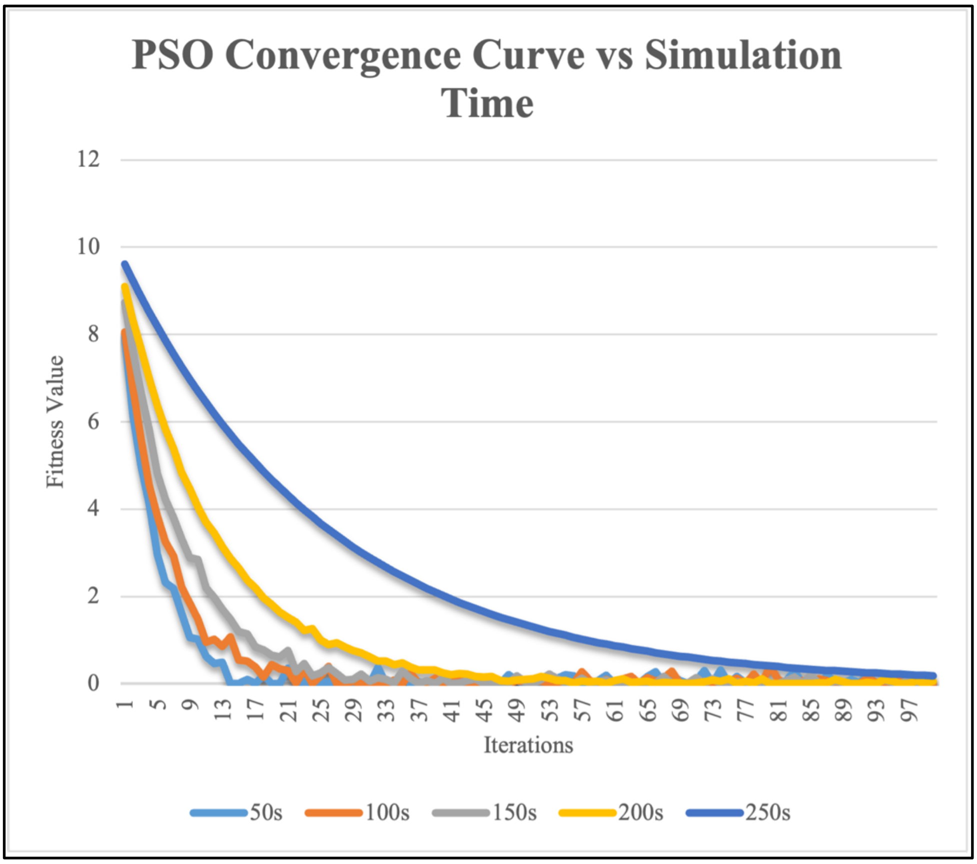



Figure 5.5 PSO Algorithm Convergence Curve vs Simulation Time

The adaptation of the PSO algorithm and improvement of fitness values over 100 iterations under various simulation periods (50s, 100s, 150s, 200s and 250s) are represented in Figure 5.5. Every curve illustrates how the performance of the algorithm stabilizes over the course of iterations and represents a scenario with a particular simulation time. From observation, the extended simulation periods give the swarm access to more environmental information and node contact possibilities, which helps it make better decisions on the data transmission. The slower convergence tail shows that the algorithm adapted well with the changing dynamic topology, mobility and also the increasing nodes. Therefore, compared to curves for shorter durations like 50s, those for longer durations such as for 200s and 250s, the algorithm tend to converge more smoothly and swiftly towards ideal fitness values. Thus, with the ability of PSO algorithm to adjust to changing circumstances, including network density and mobility in IoV network, it is proven that the proposed PSO algorithm has a stable convergence despite mobility. The longer simulation windows shows the strength of the proposed PSO algorithm in the dynamic IoV environments.

## 5.6 PSO Algorithm Convergence Curve based on the Number of Vehicles

The performance of the optimized IoV network is also examined in terms of the effect of number of vehicles. Figure 5.6 below shows the PSO algorithm convergence curve for number of vehicles.

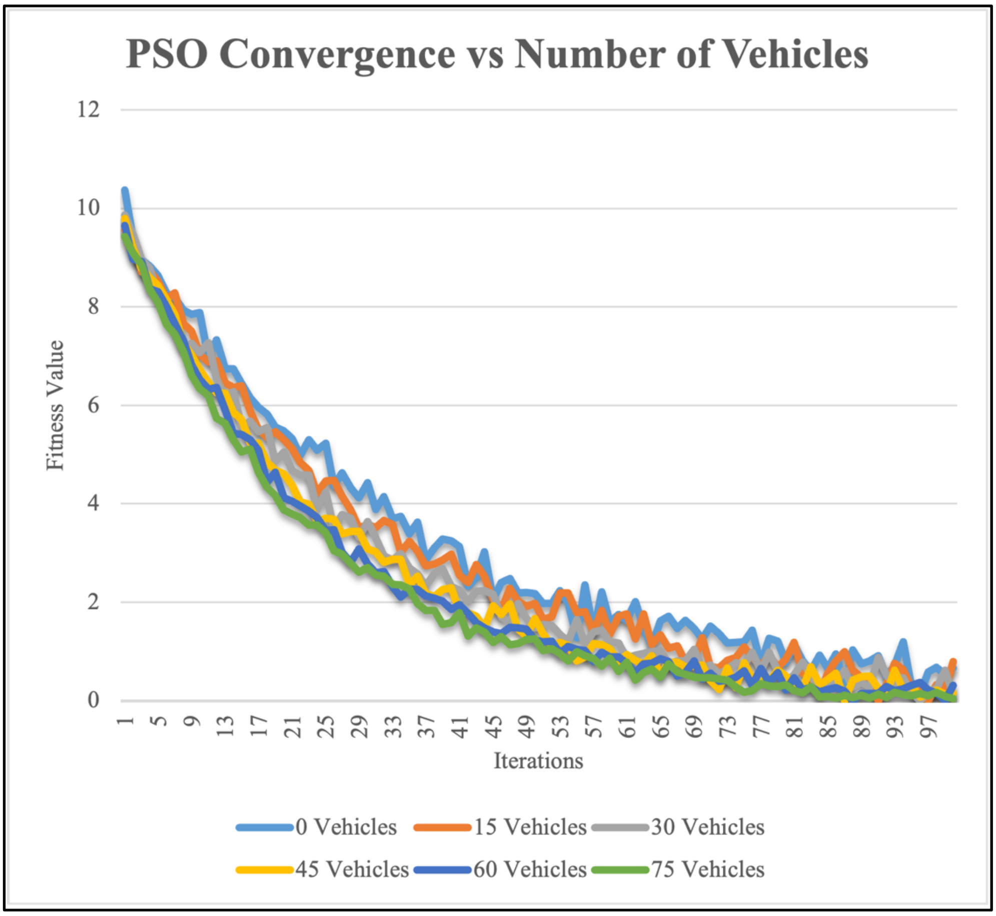



Figure 5.6 PSO Convergence Curve vs Number of Vehicles

Based on the Figure 5.6 above, the graph provides a thorough examination of the convergence behavior of the proposed PSO algorithm with respect to the number of vehicles. The data illustrates how the fitness value evolves over 100 iterations for different vehicle counts which are 0, 15, 30, 45, 60 and 75. The convergence curves demonstrated that the algorithm tends to converge more quickly and smoothly as the number of vehicles rises. The ability of the swarm in order to make decisions is enhanced as more vehicles participated in the network due to improved environmental awareness and richer data availability. The convergence is observed to be slower and more unpredictable because there is less information and feedback from the network in situations with fewer or no vehicles. This tendency is illustrated in the figure, which highlights the importance of vehicle density in maximizing swarm-based solutions for dynamic vehicular networks. The significance of node density in the design and performance adjustment of PSO algorithm for IoV applications is reaffirmed by this findings.

## 5.7 Comparative Discussion with Previous Bio-Inspired Approaches

Bio-inspired algorithms have attracted significant interest for optimizing IoV networks because their distributed decision-making and self-adaptation resemble the dynamic behavior of vehicular environments. Approaches such as ACO, GA and ABC algorithm have been used for routing, clustering and congestion control. Although these methods can achieve good solutions, they often require extensive parameter tuning and exhibit slower convergence or higher computational cost when node density and mobility increase. For example, GA depends on selection, crossover, and mutation operators and typically needs a large population to avoid premature convergence, which prolongs execution time. ACO exploits pheromone updates for path discovery but can stagnate or require careful control of evaporation rates to adapt quickly to traffic fluctuations. ABC introduced multi-phase searches that demand delicate balancing of scout or attractiveness parameters, adding to implementation overhead. Hybrid methods such as ACO-GA or ABC-DE may improve exploration but further increase algorithmic complexity and deployment cost.

Building on this, previous studies in the IoV domain have adopted bio-inspired approaches for clustering (Khan et al., 2018; Aadil et al., 2018; Rawat et al., 2017) and resource allocation (Lin & Zhang, 2022; Zhang et al., 2022). While these methods reported performance gains, most addressed QoS only indirectly through cluster stability or routing, or introduced significant implementation complexity such as bandwidth embedding and multi-domain optimization. In contrast, the proposed PSO algorithm in this study maintains a lightweight structure with only a few control parameters (inertia weight and cognitive or social coefficients) and relies on straightforward velocity and position updates. This simplicity enables rapid convergence, low computational overhead and faster adaptation to dynamic channel conditions, which are critical advantages in real-time IoV environments.

Taken together, this analysis highlights that the PSO algorithm balances biological inspiration with practical efficiency. It converges more quickly and with lower computational cost than GA, ACO and ABC algorithms, while also offering simpler implementation and greater scalability compared to traditional heuristic approaches. These strengths justify the superior performance of the proposed PSO-based congestion control framework for IoV networks.

## 5.8 Summary

This study proposes the use of the PSO algorithm as an optimization method for congestion control in IoV networks. In an urban city network scenario, a large number of packets are transmitted at high frequency and broadcasted multiple times, while many vehicles simultaneously send safety messages at similarly high rates. Such conditions inevitably lead to congestion in the communication channel, thereby affecting the performance and timely delivery of safety packets. The simulation results, conducted over different time durations and varying numbers of vehicles, demonstrate that these parameters have a direct influence on the convergence behavior of the algorithm. Specifically, as simulation time increases, the convergence rate also increases, indicating that more iterations are required for the algorithm to reach stability. Conversely, when more vehicles are present in the IoV network, the system tends to become more stabilized, which reduces the number of iterations required for convergence. This behavior is consistent with the design of the proposed PSO fitness function, where optimization is activated once the CBR exceeds 60%, enabling the system to dynamically adjust transmission rates and ensure stable network performance.

# CHAPTER 6
# CONCLUSION

## 6.1 Introduction

In this chapter, we present a summary of the research achievements by outlining some of the main points in this thesis and discussed in detail with the major contributions are highlighted. Additionally, meaningful output analysis involves using a validated simulation framework to derive information in order to draw robust conclusions on the efficiency of new concepts proposed within the research. Following that, the subsequent sections discuss future research directions based on the findings and the results of this research. This chapter is organized as follows; section 6.1 provides the overview of the thesis; section 6.2 presents an analysis of the result obtained; section 6.3 states the contribution of the research; and section 6.4 provides suggestions for future research directions.

## 6.2 Discussion of Results

A recent innovation in vehicular networks including IoV network involves using moving vehicles as nodes to establish a mobile network. This vehicular communication technology holds significant potential to enable new safety and comfort-related applications that were previously unattainable. Critical applications, such as safety systems, require high reliability and low latency to ensure messages are delivered to as many vehicles as possible.

This research was initiated with an intensive literature review in the field of vehicular networks, focusing mainly on the optimization of the IoV network. The literature review focused on two broad categories, which are the IoV network and the optimization on the network using PSO algorithm.

As congestion causes a great loss to the network in terms of throughput and packet delivery, this study prefers to focus on the prevention of congestion. The current non-optimized IoV network addressed the issues where vehicles in the network have difficulties in maintaining a consistent connection with each other due to variety and rapid mobility characteristics of the IoV network. When more nodes get connected to the same network, the strength of the network will start to loosen and this will affet the QoS performance of the network in disseminating safety-related message to the neighboring nodes. The proposed optimized IoV network can reduce the delay of data traffic that cause redundancy and collisions by eliminating packets flooding. In addition, the throughput and the PDR can be increased thus improving the overall performance where network congestion can be avoided.

The extensive literature review has guided the research in the formation of the research problem and the research methodology. The research methodology explains the design and comparative framework of this study. The research design compromises on the significant component of the optimization method. The design process involves a discussion of the development of an efficient optimized IoV network. This is followed by the implementation of the proposed optimization in the simulation environment of the SUMO and OMNeT++ simulator. In the evaluation phase, a detailed comparison of the non-optimized and the proposed optimized IoV network was conducted. The detailed performance of the proposed scheme was evaluated based on the packet throughput, PDR and packet delay. The proposed work optimized the transmission rate and the delay was selected as the objective function to be minimized, which emphasize on the end-to-end congestion control. The rationale to run the test is to examine the impacts of the proposed optimized IoV network, thus demonstrate improvements of the performance of the IoV network, ensuring faster communication between vehicles. This is vital for real-time applications like autonomous driving. Finally, the details of the performance of the proposed optimized IoV network scheme is represented.

The key advantage of the simulation studies and the theoretical analysis is to provide implementation-dependent results, as compared to prototype, hardware or real development based approaches. The evaluations were carried out using the OMNeT++ simulator as an evaluation platform because it provides the best functionality for IoV network modelling with a number of key advantageous features. It is a public source simulator with generic and flexible architecture, reliable and flexible on a component-based simulation package, class library, graphical network editing and animation, data collection, graphical representation of simulation data and random number generator. Nevertheless, it has become a popular simualation platform in both scientific and industrial communities, since the tool is workable with various operating systems and C++ compilers.

The first and second contributions of this study are discussed in Chapter 4. In particular, this study has proposed an efficient optimized IoV network scheme to reduce the delivery delays of safety messages in a realistic city vehicular scenarios. The IoV network and the optimization algorithm are integrated to developed an efficient IoV network optimization scheme to increase the packet throughput and delivery of the network. The proposed optimized IoV network shows satisfactory performance in the vehicular environment that was tested. The result from the extensive simulations demonstrated that the proposed optimization on the network shows promising performance compared to the conventional non-optimized IoV network.

Chapter 5 describes the third contribution of this research. In the context of network performance optimization, the metrics of throughput, packet delivery ratio (PDR), and delay were rigorously evaluated and tested. Throughput, a critical metric, refers to the amount of data successfully transmitted from source to destination within a specific timeframe, and it is essential for assessing the capacity of the network to handle high data loads efficiently. The PDR, another important metric, is the ratio of data packets successfully delivered to their intended destination against the total number of packets sent, serving as a key indicator of network reliability and effectiveness in avoiding packet loss. Delay measures the time it takes for data packets to traverse the network from source to destination, and minimizing this delay is crucial for safety applications requiring real-time data transmission.

PSO was employed as a powerful optimization technique to enhance these metrics by searching for the optimal network parameters that balance the throughput, PDR, and delay. By simulating in different network parameters, PSO iteratively adjusted the transmission power as the network becomes densed, striving to maximize throughput and PDR while minimizing delay. The outcome of this optimization process was a set of network configurations that significantly improved overall performance, ensuring high data transfer rates, reliable packet delivery, and reduced latency, ultimately leading to a more efficient and responsive network.

## 6.3 Achievements

In summary, the major achievements of the research are:

i. The achievement of developing an optimized Internet of Vehicles (IoV) network that executes the Particle Swarm Optimization (PSO) algorithm represents a significant advancement in the field of intelligent transportation systems. In this research, the IoV network is designed to enhance communication and data exchange among vehicles within a vehicular network. By integrating the PSO algorithm into the network, the proposed approach is capable of dynamically optimizing transmission rate of the network to obtain better throughput, PDR and reduced delay.

ii. PSO algorithm which is inspired by the social behavior of birds flocking, is a powerful optimization technique that iteratively searches for the best solutions by adjusting the positions of particles (representing possible solutions) in the search space. In the context of IoV network, these particles represent different network configurations. The PSO algorithm evaluates the performance of these configurations based on key metrics such as throughput, PDR and delay. The objective function proposed in the PSO algorithm put a significant contribution in optimizing the IoV network and produced better outputs compare to the non-optimized network. Through continuous iteration, the algorithm converges on an optimal set of parameters that maximize network efficiency, ensuring reliable and high-speed communication among vehicles. This approach not only enhances the performance of vehicular networks by reducing latency and improving data transmission reliability, but also contributes to congestion prevention and more efficient transportation system. The ability to dynamically adapt to changing network conditions in real-time makes this network particularly valuable in scenarios such as urban traffic management, autonomous driving, and emergency response, where quick and reliable communication is crucial.

## 6.4 Contribution

In a dense IoV network, a large number of vehicles broadcast safety packets generated at a high frequency. Therefore, the CCH communication channel, which is responsible for safety messages tends to be easily congested. It is crucial for the CCH communication channel to be free from congestion in order to ensure timely and reliable delivery of safety-based messages. The optimization scheme for congestion control is one of the solutions to prevent congestion in the CCH communication channel. The proposed optimization scheme and algorithm will improve the performance of the dissemination of safety messages. In addition, this research focuses on the safety packets with similar high priority.

Previous studies have addressed CCH congestion control using methods such as adaptive beaconing, transmission-power control, multiplicative rate-decreasing algorithms and other bio-inspired approaches including GA, ACO and ABC. While these techniques achieved partial success, many suffered from high computational cost, slow convergence, or limited scalability under highly dynamic vehicular mobility, making real-time deployment challenging.

Building on these limitations, benchmark studies such as the clustering approach by Khan et al. (2018) and the bandwidth allocation framework by Zhang et al. (2022) have demonstrated how bio-inspired and resource optimization methods can improve IoV network performance. However, both approaches highlight trade-offs between performance and complexity. While clustering improves stability, it indirectly addresses QoS and while bandwidth embedding enhances resource utilization, it introduces substantial implementation overhead. These studies therefore provide a valuable benchmark for positioning the proposed PSO-based congestion control framework, which directly optimizes communication parameters to improve throughput, PDR and delay while maintaining simplicity and scalability.

In this research, an efficient optimization scheme for the purpose of congestion control in IoV network has been proposed and developed. An enhancement of the PSO algorithm is performed to moderate the congestion issue by limiting the forwarded traffic in the realistic city vehicular environment. This work leverages the characteristics of PSO algorithm, namely fast convergence and low computational complexity, together with dynamic transmission rate adjustment to overcome the limitations observed in earlier heuristic and metaheuristic approaches. The outcomes of the simulation confirm that the suggested optimization scheme provides traffic without congestion and upholds fairness among the neighboring nodes. The packet load transmission is made as fast as possible without causing CCH congestion in the IoV network. Furthermore, the simulation results show the adaptability of the proposed optimized scheme to dynamic changes compared to the conventional IoV network. The observation on the average improvement of 23.13% and 13.91% in simulation time and number of vehicles for throughput factors respectively. In terms of PDR, the proposed IoV network optimization scheme performs better where it recorded an improvement of 37.46% for simulation time and 15.1% for number of vehicles. Finally, an improvement of 12.22% and 15.3% delay are identified in simulation time and number of vehicles respectively. These findings confirm that the proposed PSO-based optimization not only addresses the shortcomings of prior heuristic and bio-inspired methods but also establishes a practical and scalable benchmark for real-time IoV network congestion control.

In conclusion, the findings of this study demonstrate that a robust and intelligent optimization mechanism for congestion control is indispensable for supporting safety applications in city-based vehicular IoV networks. The proposed mechanism effectively prevents congestion on the CCH channel in practical vehicular environments, thereby ensuring reliable communication. Moreover, the results justify the applicability of the scheme in realistic traffic scenarios, highlighting its potential for real-world deployment. These findings can be further leveraged to develop commercial solutions that can be embedded into vehicles, ultimately enhancing the performance of vehicular networks in handling both multimedia and commercial data traffic.

## 6.5 Future Directions and Research Opportunities

This thesis achieves various objectives through the development of the QoS awareness (throughput, PDR and packets delays) of IoV network environment. As witnessed in the previous chapters, the developed approach has performed better compared to the non-optimized network in vehicular environment. However, the developed solutions still need improvement and can be considered as underpinnings of the emerging vehicular communication technologies that will certainly eclipse the market in the near future.

In conclusion, we have investigated the approach to improve the throughput, PDR and packet delay in the IoV network. Importantly, this study has shed light on the future directions of potential research in this area. Some of the specific directions are presented in the following sections.

### 6.5.1 Communication Channel

The vehicle selection algorithm for V2V communication was presented in this thesis. However, V2I communication was not included in the current analytical model and simulation. Future research could extend the proposed optimized IoV framework to evaluate its performance in V2I environments, examining how communication between vehicles and infrastructure affects overall network efficiency, congestion control and QoS.

### 6.5.2 Enhanced PSO Algorithm

An enhanced PSO algorithm for the optimization of IoV network can significantly improve network performance by addressing the unique challenges posed by vehicular networks, such as high mobility, dynamic topology and varying communication environments. Key enhancements include dynamic particle adaptation, which allows the algorithm to quickly respond to real-time changes in the network topology, and multi-objective optimization, enabling the algorithm to simultaneously optimize for multiple metrics; throughput, PDR and delay. Adaptive inertia weight in the PSO algorithm can be further refine the algorithm by balancing exploration and convergence based on the optimization phase, while dynamic neighborhood topology variations adjust the communication between particles depending on network density and vehicle distribution. A hybrid approach, combining PSO algorithm with other optimization techniques such as GA, ACO algorithm, ABC algorithm or other suitable bio-inspired algorithms can exploit the strengths of each method for more robust solutions.

### 6.5.3 Autonomous Driving Scenarios

The utilization of autonomous vehicles is suggested to minimize the packet delay and maximize the throughput and PDR. In our study, all vehicles are assumed as autonomous. However, this is considered impractical assumption in reality. Therefore, future research direction could include developing a model for a city and also another environment which is highway with hybrid vehicles where it combines both autonomous and regular vehicles. Nevertheless, this problem can be modelled after IoV network in such way that include both static and mobile nodes, where regular vehicles are considered as relatively static and autonomous vehicles are considered as the mobile nodes.

### 6.5.4 Smart Cities

Smart cities solution rely heavily on the IoV architecture, which offers creative ways to improve efficiency, safety, and urban mobility. IoV network enhances traffic management by providing real-time data transmission between infrastructure, city management systems, and cars. This results in several cases such as optimal vehicle network and routing and dynamic traffic signal regulation, which lowers travel times and congestion. By enabling communication between vehicles and infrastructure, it also improves road safety by resulting in better collision avoidance systems and hazard notifications. IoV network also facilitates the combination of autonomous and electric vehicles, fostering environmentally friendly urban mobility. Cities can become smarter, safer, and more sustainable by utilizing resources more efficiently thanks to this interconnected ecology.

### 6.5.5 Security

The key elements of any vehicular communication system are its security level and susceptibility to possible attacks. Additionally, energy-aware PSO algorithm optimizes configurations to minimize energy consumption, critical for extending the operational lifetime of network components, and security-enhanced algorithm incorporates security objectives to protect against potential threats. Together, these enhancements make the algorithm more effective and resilient for the dynamic and demanding environment of IoV network, leading to improved reliability, efficiency, and security in vehicular communications.

In order to protect the confidentiality and validity of the data transferred in mobile network environments, a study on the security implications and development technique for vehicular networks can be further expanded.

## 6.6 Summary

This chapter concludes and summarizes the research conducted and discussed throughout this thesis. It highlights the significant findings and contributions, particularly the development of a robust and intelligent PSO-based optimization mechanism that effectively prevents congestion on the CCH channel in practical vehicular environments. The study not only demonstrates the applicability of the proposed scheme in realistic traffic scenarios but also establishes a foundation for future advancements in congestion prevention and optimization within IoV networks.

For future research, several directions can be pursued. First, multi-objective optimization techniques can be explored to jointly optimize delay, energy efficiency and fairness alongside congestion control. Second, integration with emerging communication technologies such as 5G, 6G and edge computing can further enhance scalability and real-time responsiveness. Third, the combination of PSO algorithm with machine learning or reinforcement learning approaches offers the potential to improve adaptability in highly dynamic environments. Finally, broader testing in large-scale and heterogeneous vehicular scenarios can validate the robustness of the framework and accelerate its transition into commercial deployment.

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