

Novel Internet of Vehicles Approaches for Smart Cities



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Abstract

Smart cities are the domain where many electronic devices and sensors transmit data via the Internet of Vehicles concept. The purpose of deploying many sensors in cities is to provide an intelligent environment and a good quality of life. However, different challenges still appear in smart cities such as vehicular traffic congestion, air pollution, and wireless channel communication aspects. Therefore, in order to address these challenges, this thesis develops approaches for vehicular routing, wireless channel congestion alleviation, and traffic estimation.

A new traffic congestion avoidance approach has been developed in this thesis based on the simulated annealing and TOPSIS cost function. This approach utilizes data such as the traffic average travel speed from the Internet of Vehicles. Simulation results show that the developed approach improves the traffic performance for the Sheffield scenario in the presence of congestion by an overall average of 19.22% in terms of travel time, fuel consumption and CO_2 emissions as compared to other algorithms.

In contrast, transmitting a large amount of data among the sensors leads to a wireless channel congestion problem. This affects the accuracy of transmitted information due to the packets loss and delays time. This thesis proposes two approaches based on non-cooperative game theory to alleviate the channel congestion problem. Therefore, the congestion control problem is formulated as a non-cooperative game. A proof of the existence of a unique Nash equilibrium is given. The performance of the proposed approaches is evaluated on the highway and urban testing scenarios.

This thesis also addresses the problem of missing data when sensors are not available or when the Internet of Vehicles connection fails to provide measurements in smart cities. Two approaches based on l_1

norm minimization and a relevance vector machine type optimization are proposed. The performance of the developed approaches has been tested involving simulated and real data scenarios.

Acknowledgement	iii
Abstract	v
Abbreviations	xi
List of Symbols	xvii
List of Figures	xxiii
List of Tables	xxv
1 Introduction	1
1.1 Motivation	1
1.2 Vehicular Traffic Congestion Avoidance Approaches for Smart Cities	2
1.3 The Communication Network Congestion Problem	5
1.4 Filtering and Predication of the Traffic State	8
1.5 Contributions	10
1.6 Thesis Outline	12
1.7 List of Publications	14
2 Background and Literature Review	17
2.1 Mathematical Background	17
2.1.1 The Simulated Annealing Approach	17
2.1.2 The Multi Attribute Decision Making	18
2.1.3 The Newton-Raphson Method	19
2.1.4 Game Theory Fundamentals	20
2.1.5 Compressive Sensing and Bayesian Compressive Sensing .	21
2.2 Challenges in Intelligence Transportation Systems	22
2.3 Route Selection to Avoid Vehicular Traffic Congestion via Multi-Objective Optimization	22

2.3.1	Traffic Congestion Avoidance Routing Approaches	23
2.3.2	Road Traffic Congestion Detection via IoV	26
2.4	Game Theoretic Approaches to Resolving Congestion in The Communication Network	31
2.4.1	Adaptation via Data Rate	31
2.4.2	Adaptation via Power Transmission	36
2.4.3	Adaptation via MAC Channel Mechanism	38
2.4.4	Adaptation via Hybrid Approaches	39
2.5	Particle Filtering and Compressive Sensing for State Estimation .	41
3	Traffic Congestion Avoidance Approach	45
3.1	Introduction	45
3.1.1	Main Contributions	46
3.2	System Description	47
3.2.1	Data Dissemination	48
3.2.2	Road Network Formulation	48
3.2.3	The Simulated Annealing for Routing Avoidance	49
3.2.4	An Improved Simulated Annealing for Routing Avoidance	51
3.2.5	Approaches for Weights Calculation	53
3.2.6	Simulated Annealing Weighted Sum Approach	55
3.2.7	TOPSIS Cost Function Formulation	55
3.3	Performance Evaluation	56
3.3.1	Scenario of Sheffield City	57
3.3.2	Scenario of Birmingham City	67
3.4	Conclusions	70
4	A Game Theory Approach for Congestion Control in Vehicular Ad Hoc Networks	73
4.1	Introduction	73
4.2	System Description	76
4.2.1	A Game Theory Approach Formulation:	76
4.2.2	The Utility Function Formulation	78
4.2.3	Nash Equilibrium Proof and Existence	80
4.3	The Solution Calculation of the VANET Game	84
4.3.1	GTACC approach implementation	85

4.3.2	NCGACC Approach Implementation	87
4.4	Performance Evaluation of GTACC	88
4.4.1	Parameters Selection of the Game Approach	91
4.4.2	Highway Simulation Scenario	92
4.4.3	Urban Simulation Scenario	96
4.5	Performance Evaluation of NCGACC	100
4.5.1	An Approach Parameters Selection	100
4.5.2	NCGACC Simulation Results	100
4.5.3	A Highway Scenario	102
4.5.4	An Urban Scenario	108
4.6	Conclusions	114
5	Filtering and Predication of Traffic Flow	117
5.1	Introduction	117
5.2	Traffic Flow Models	119
5.2.1	A Stochastic Traffic Model	119
5.2.2	The Measurements Model	122
5.3	Dealing with the Missing Measurements	122
5.3.1	Compressive Sensing	122
5.3.2	Bayesian Compressive Sensing	124
5.4	Particle Filtering Framework for Traffic State Estimation	128
5.4.1	The Particle Filter Approach	128
5.5	Performance Evaluation	131
5.5.1	Evaluation of CS and BCS based measurements estimation methods	131
5.5.2	Evaluation of Traffic State Estimation performance	133
5.6	Conclusions	142
6	Conclusion and Future Work	143
6.1	Conclusions	143
6.2	Limitations	145
6.3	Future Work	146
	References	148

- ABR** Adaptation Beacon Rate
- ACO** Ant Colony Algorithm
- AHP** Analytical Hierarchy Process
- AOS** Adaptable Offset Slot
- AMRC** Adaptive Message Rate Control
- ATB** Adaptive Traffic Beacon
- ATT** Average Travel Time
- AVCAS** Ant-Based Congestion Avoidance System
- AWT** Average Waiting Time
- BCS** Bayesian Compressive Sensing
- BRR** Beacon Reception Rate
- CAM** Cooperative Awareness Messages
- CBR** Channel Busy Ratio
- CCH** Control CHannel
- COC** Contents Oriented Communication
- CoTEC** Cooperative Traffic Congestion Detection
- CTM** Cell Transmission Model
- CS** Compressive Sensing
- CSA-VIKOR** Centralized Simulated Annealing VIKOR

CSMA/CA Carrier-Sense Multiple Access with Collision Avoidance

DA Dijkstra Algorithm

D-DA Dynamic Dijkstra Algorithm

DENM Decentralized Environmental Notification Messages

DSP Dynamic Shortest Path

DSRC Dedicated Short Range Communication

EKF Extended Kalman Filter

FABRIC Fair Adaptive Beaconing Rate for Inter-vehicular Communications

FC Fuel consumption

FPAV Fair Power Adjustment for Vehicular environment

GARUDA Geographical Accident Aware of Reducing Urban Congestion

GTACC Game Theory Approach for Congestion Control

IoT Internet of Things

IoV Internet of Vehicles

ISATOPSIS Improved Simulated Annealing Technique for Order Preference by Similarity to Ideal Solution

ITSs Intelligent Transportation Systems

JFI Jain's Fairness Index

KB knowledge Base

KFs Kalman Filters

KKT Karush Kuhn Tucker

LOS Level of Service

LTE-V Long Term Evolution-Vehicle

MADM Multi-Attribute Decision Making

MACO Modified Ant Colony Optimization

MCDM Multi-Criteria Decision Making

MCMC Markov chain Monte Carlo

MTD Mean Travel Distance

MTT Mean Travel Time

NCGACC Non-Cooperative Game Approach for Congestion Control

NFC Near Field Communication

NIS Negative Ideal Solutions

NORAC Non-cooperative Beacon Rate and Awareness Control

NUM Network Utility Maximization

ODA Original Dijkstra Algorithm

QoS Quality of Service

OSM Open Streets Map

PDF Probability Density Function

PPDF Posterior Probability Density Function

PDR Packet Delivery Ratio

PFs Particle Filters

PIS Positive Ideal Solutions

PULSAR Periodically Updated Load Sensitive Adaptive data Rate

RKSP Random Multipath K Shortest Paths

RSU Road Side Unit

RVM Relevance Vector Machine

SA Simulated Annealing

SATOPSIS Simulated Annealing Technique for Order Preference by Similarity to Ideal Solution

SAWS Simulated Annealing Weighted Sum

SCM Stochastic Compositional Model

SCORPION Solution using COoperative Re-routing to Prevent Congestion and Improve traffic Condition

SD Standard Deviation

SNR Signal to Noise Ratio

SOTIS Self-Organizing Traffic Information System

SUMO Simulation of Urban Mobility

TD Travel Distance

TIS Traffic Information System

TMC Traffic Management Centre

TMSs Traffic Management Systems

TraCI Traffic Control Interface

TT Travel Time

UKF Unscented Kalman Filter

V2I Vehicle to Infrastructure

V2V Vehicle to Vehicle

VANETs Vehicular Ad Hoc Networks

VRP Vehicle Route Problem

WAVE Wireless Access of Vehicle Environment

WSN Wireless Sensor Networks

l_1 Norm minimisation

L_i The length of road segment i

\mathbf{x}_k State vector of traffic parameters

$N_{i,k}$ Number of vehicles

$v_{i,k}$ Average speed

$n + 1$ Fictitious last road segment

f_i Function of traffic model

$\boldsymbol{\eta}_k$ random fluctuations and modelling error

Q_k^{in} Vehicles entering the first segment

Q_k^{out} Vehicles leaving the last segment

Δt_k time interval

$S_{i,k}$ Sending function vehicles intend to leave cell i

$R_{i,k}$ Receiving function representing the maximum number of vehicles that are allowed to enter cell $i + 1$

$N_{i+1,k}^{max}$ maximum number of vehicles that can be present simultaneously in cell i

A_ℓ Average length of vehicle

t_d Minimal safety time distance between vehicles

$N_{i,k+1}$ Updated the number of vehicles in a cell

$v_{i,k+1}$ Updated the average speed of vehicles in a cell

$\rho_{i,k+1}^{antic}$ Updated density

α weight coefficient

$\eta_{v_i,k+1}$ A noise reflecting the fluctuations in the drivers speed

$v^e(\rho_{i,k+1}^{antic})$ speed–density relation

\mathbf{z}_s measurement vector

z_j, s measurement equation

ξ_s Error Gaussian distribution

$\mathbf{x}_0^{(l)}$ Generated samples from the initial distribution

$w_0^{(l)}$ Particle filter samples initial weights

$w_s^{(l)}$ Particles weights

$\hat{w}_s^{(l)}$ Normalize weights

$\hat{\mathbf{x}}_s$ Output vector

\mathbf{M}_s Measurement matrix

\mathbf{b}_s Vector identify the measurements available or unavailable

$\hat{\mathbf{z}}_s$ Current measurements

$\tilde{\mathbf{z}}_s$ Mean of the historical measurements

ϕ_s Relevant historical measurements/estimates

$\hat{\mathbf{z}}_{k,CS}$ Final estimate

σ^2 Variance

\mathbf{p}_s Hyperparameters to be estimated

Σ_s The covariance matrix

$\boldsymbol{\mu}_s$ Mean value

\mathbf{Z}_a Measurements matrix
 K_a The number of points in the decomposed matrix
 G Road network or directed graph
 N Corresponds to the intersections (Nodes) on the graph
 E Corresponds to the road segments (edges) on the graph
 A The road matrix
 n The number of roads in the road matrix
 j The number of attributes of each road in the road network
 r_{kj} The normalized road matrix
 r The normalized performance values of each C_L and C_S
 X Denotes the set of performance values of each C_L and C_S
 w Denotes the set of weights
 V The set of vehicles
 msg_j Corresponds to the message send periodically by each vehicle
 C_L Road Length
 C_S Average Velocity
 K The random paths have been generated from matrix A
 R_k The matrix of K random paths generated from A
 X_c The current solution, which is generated randomly from A
 T Denotes the temperature parameter of simulated annealing algorithm
 α Denotes the cooling rate of simulated annealing algorithm
 X_n The new solution generated randomly

$N(X_n)$ The cost function of the new solution
 $C(X_c)$ The cost function of current solution
 s_b Current best solution
 T_m The minimum temperature of simulated annealing algorithm
 P_t The transition probability
 R'_{kj} Range normalization
 M' The matrix after range normalization
 r_{kj} Values of the criterion (j) in C_L and C_S
 \bar{R}_j The mean of the values of the j^{th} criterion in C_L and C_S after normalization
 w_j the weight of the criterion(j) in road matrix A
 SDV_j The standard deviation that is calculated independently for every j^{th} criterion
 f The weighted sum cost function of the simulated annealing
 z_{kj} The weighted normalized ratings of TOPSIS cost function
 H^+ Positive Ideal Solutions
 H^- Negative Ideal Solutions
 D_k^* The separation from positive Ideal Solutions
 D_k^- The separation from negative Ideal Solutions
 Y_k^* The TOPSIS cost function of simulated annealing algorithm
 n vehicles (players)
 r_i Sending rate of vehicle
 w_1 weight parameter
 w_2 weight parameter

V A group of vehicles
 S_i Available strategies for vehicle
 χ_i The utility function of vehicle
 $U_i(r_i)$ The payoff function of vehicle
 $P_i(r_i; p_i)$ The priority function of vehicle
 D_{ij} The distance between the original sender and the receiver
 R The transmission range
 α_i The player preference parameter
 π_i The player preference parameter
 r_i^* The optimal game solution
 C The Maximum Data Load
 λ_i The Lagrange multipliers
 ξ_i The Lagrange multipliers
 $C_i(r_i; c_i)$ Maximum contention delay
 Θ_i A twice continuously differentiable utility function
 $H(s)$ The Hessian matrix
 β_i The player preference parameter
 $G(r_i, r_{-i}; q)$ The Jacobian matrix

List of Figures

1.1	The IoV vision [5]	2
2.1	Taxonomy of traffic congestion avoidance in smart cities.	23
2.2	Taxonomy of traffic congestion detection systems based on VANETs.	27
2.3	Taxonomy of adaptive safety messages approaches	32
3.1	IoV road network infrastructure	47
3.2	The procedure of generating a random path	51
3.3	The procedure for constructing a new path X_n based on an initial path X_c	53
3.4	Flow chart of the SA congestion avoidance mechanism	54
3.5	The city centre of Sheffield and SUMO map	59
3.6	The zoomed places showing traffic congestion on some roads	60
3.7	Average travel time	64
3.8	Average travel distance	65
3.9	Average fuel consumption	65
3.10	Average CO2 emission	66
3.11	Average travel speed	67
3.12	The section of Birmingham city centre and SUMO map	68
3.13	Average travel time Birmingham scenario	69
3.14	Average fuel consumption Birmingham scenario	70
4.1	Diagonal Strict Concavity [139].	83
4.2	The flow chart of congestion control in VANET	89
4.3	α_i vs CBR.	92
4.4	α_i vs data rate.	92
4.5	π_i vs CBR.	93
4.6	π_i vs data rate.	93
4.7	A Example scenario considered in SUMO.	94

4.8	Total average throughput	94
4.9	Total average delay	95
4.10	Total number of lost packets	95
4.11	Total channel busy time	96
4.12	The considered urban scenario of the evaluated approaches	97
4.13	Average throughput of evaluated approaches in the urban scenario	97
4.14	Average delay of evaluated approaches in the urban scenario	98
4.15	Packets loss of evaluated approaches in the urban scenario	99
4.16	The busy time of evaluated approaches in the urban scenario	99
4.17	α_i vs CBR.	101
4.18	α_i vs data rate.	101
4.19	β_i vs CBR.	101
4.20	β_i vs data rate.	101
4.21	π_i vs CBR.	101
4.22	π_i vs data rate.	101
4.23	A highway scenario considered in SUMO.	103
4.24	Total average throughput in the highway scenario	105
4.25	Total average delay in the highway scenario	105
4.26	Total number of lost packets in the highway scenario	106
4.27	Collision probability in the highway scenario	107
4.28	Packet delivery ratio in the highway scenario	107
4.29	Jain's fairness index in the highway scenario	108
4.30	CPU time in the highway scenario	109
4.31	An urban scenario considered in SUMO	109
4.32	Total average throughput in the urban scenario	110
4.33	Total average delay in the urban scenario	111
4.34	Total number of lost packets in the urban scenario	112
4.35	Collision probability in the urban scenario	112
4.36	Packet delivery ratio in the urban scenario	113
4.37	Jain's fairness index in the urban scenario	113
4.38	Packets Arrival Rate	114

5.1	Road segments and measurements points [21]. $Q_{i,k}$ is the number of vehicles crossing the boundary between segments i and $i + 1$ at time k , $N_{i,k}$ and $v_{i,k}$ the number of vehicles and average of the vehicles, respectively.	118
5.2	MFD flow-density relationship	119
5.3	MFD speed-density relationship	120
5.4	Schematic of Belgium freeway considered [21]. CLOF-CLO9 show the locations of cameras used to make the traffic measurements	132
5.5	Traffic density RMSE for CLOE, the solid line is for the PF using 2 measurements only and the dashed line with the BCS estimated measurements.	134
5.6	Traffic density RMSE for CLOC, the solid line is for the PF using 2 measurements only and the dashed line with the BCS estimated measurements.	135
5.7	Traffic velocity RMSE for CLOE, the solid line is for the PF using 2 measurements only and the dashed line with the BCS estimated measurements.	136
5.8	Traffic velocity RMSE for CLOC, the solid line is for the PF using 2 measurements only and the dashed line with the BCS estimated measurements.	137
5.9	NRMSE for the traffic density in COLE and COLC.	138
5.10	NRMSE for the traffic velocity in COLE and COLC.	139
5.11	Flow-density diagram for the PF with 2 measurements available.	141
5.12	Flow-density diagram for the PF with the BCS estimated measurements.	141

3.1	Simulation parameters as configured in the SUMO implementation of Sheffield scenario	57
3.2	The tuned SA algorithm parameters of off-line and on-line search	58
3.3	The average results obtained by DA, SAWS, SATOPSIS and ISATOPSIS in the tested scenarios	62
3.4	The overall average variance results obtained by all algorithms in the tested scenarios	63
3.5	The simulation parameters configured in the SUMO of Birmingham city	69
4.1	Configuration parameters for the implemented example	91
4.2	Configuration parameters for the implemented examples	104
5.1	Performance summary for the CS and BCS based measurements estimation methods with simulated data.	132
5.2	Performance summary for the CS and BCS based measurements estimation methods with real data.	133
5.3	Performance summary for PF with 2 measurements available and the BCS estimated measurements.	140

1.1 Motivation

Smart cities are systems of systems that face challenges, especially in transport, energy and communications aspects and necessitates digital and physical infrastructures that are resilient to changes. Providing efficient mobility solutions requires Internet of Things (IoT) and Internet of Vehicles (IoV) technologies. The IoT and IoV provide platforms for data collection, communication and decision making. However, the road traffic congestion is still considered as a serious problem that is generated due to increase of the number of vehicles. This problem has affected many factors of the travel journey such as the cost of the path, the time needed to travel, increases in the fuel consumption and air pollutions. According to [1], the first most common cause of time delay, fuel consumption, the wasted time and money in the worldwide is vehicle traffic congestion.

However, the appearance of IoT and IoV have provided a new direction for intelligent transportation applications. The IoT is an envisaged communication system that allows various devices such as Wireless Sensor Nodes (WSNs), mobile phones, mobile phone masts, actuators and near field communication (NFC) devices to communicate and collaborate with each other to complete a common goal [2]. The IoV technology as part of IoT, foresees all future vehicles to be connected, sharing information to improve traffic safety and mobility. The IoV include many devices such as on boards unit on vehicles, a Road Side Unit (RSU), magnetic and induction loop sensors, WSNs, magnetometer and infrared sensors. Figure 1.1 illustrates the IoV vision. Intelligent Transportation Systems (ITSs) is considered as one of the most important applications in the IoV [3]. IoV is a promising platform that offers a solution for the design of an efficient traffic control systems. Therefore, traffic state estimation and prediction and road traffic congestion avoidance approaches are two of the most recent issues in ITSs [4]

1. INTRODUCTION

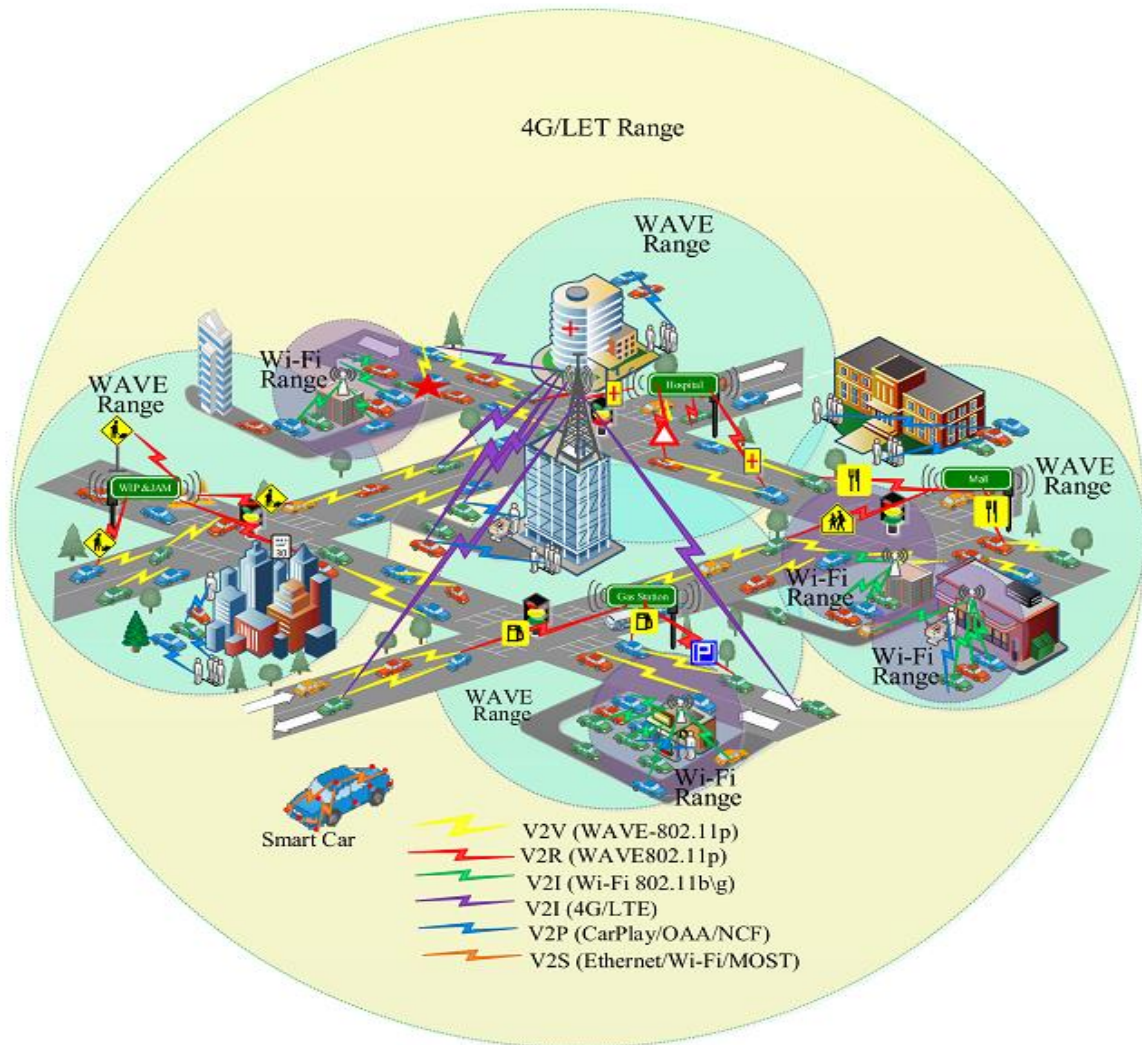


Figure 1.1: The IoV vision [5]

which plays an essential role in reducing the travel time, fuel consumption and improve the road transport safety.

1.2 Vehicular Traffic Congestion Avoidance Approaches for Smart Cities

The explosive growth of the global economy has led to an expansion of cities. There has been a huge growth in the public mass and that leads to increase the number of vehicles driving on city road networks of limited capacity. This

1.2 Vehicular Traffic Congestion Avoidance Approaches for Smart Cities

has prompted an extreme increase in road traffic congestion, road accidents, and air pollution. Some studies have revealed that 30% of CO_2 emissions are due to inefficient vehicle management [6]. This has resulted in significant economic and productivity losses, making improvement of mobility a key challenge within smart cities. Solving such a problem can be aided by information obtained via sensors deployed as part of smart city initiatives, which then have to be communicated to vehicles/drivers to allow them to make a decision with regards to alternative routes. Once such a decision had been taken, it would also be feasible to eventually see information regarding planned routes to be communicated back from the vehicles to the smart city infrastructure. Such information can then be used to predict the number of vehicles at each intersection within a smart city, which in turn could be used to adapt the sequences of traffic lights to allow a more overall optimal traffic flow for the city as a whole. A further example of how this can be used within smart cities would be related to reducing the concentrations of air pollution with the city. This would be achieved by redirecting heavily polluting vehicles away from areas with high pollution levels.

As a result, there has been a significant body of research dealing with the algorithms to reduce traffic jams. The Dijkstra [7] and the A* algorithms [8] are the two most common path planning algorithms. Other studies concentrate on the integration of swarm intelligent algorithms, such as artificial ant colony algorithms [9], genetic and simulated annealing algorithms [10]. However, most of the recently developed algorithms are generally designed for static graphs. They are not designed to be employed for dynamic path planning in a real-time traffic environment. This is due to the unpredictable traffic conditions that might occur in the dynamic environment.

Recently, hybrid systems have been suggested to integrate algorithms in each group to create a vigorous integrated solution to overcome any drawbacks or obstructions on every single approach. For example, the hybrid genetic algorithm using Dijkstra's heuristic multi-objective optimization for dynamic route planning with the predicted traffic in a real-world road network [11].

There is a significant increase in developing effective solutions for improved mobility in ITSs [12]. Finding the optimal navigation route, from a source to a destination within a reasonable time is the key task. Different cost functions can be applied such as attaining the minimum travel distance (TD), minimum travel

1. INTRODUCTION

time (TT) or minimum fuel consumption. ITSs is comprised of a broad range of wireless communication-based information, control, and technologies. When combined with the transportation system infrastructure and in vehicles themselves, this technology helps to manage traffic flow, reduce traffic jams, enhance road safety, provide alternative routes to commuters, reduce fuel consumption, time, money and vehicle emissions in congested urban areas [13].

An efficient approach can be developed with the aid of IoV. Vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communication systems are two subset of IoV. The V2V communication system allows two vehicles to interact directly without relying on fixed infrastructure. On the contrary, the V2I communication system allows vehicles to communicate with the RSU such as sensors, traffic light controllers, intelligent signals and mobile phone masts etc are installed as part of the smart city concept [14]. V2V and V2I have been widely utilized to resolve various complications related to transportation in smart cities, in which the most significant problem is road traffic congestion.

IoV systems can significantly improve traffic safety and convenience in smart cities, by providing drivers with timely information about road conditions and travel situations. Existing solutions to road traffic congestion problem by utilizing vehicular communication rely either on V2V communication alone or both V2V and V2I communications. However, there are still some Limitations, which can be summarized as follows:

1. A large portion of the previous or current vehicle routing algorithms attempt to identify the minimum TD or TT. Generally, they cannot attain an active trade-off.
2. Utilizing just individual traffic information or a single cost function for vehicle routing problem is not satisfactory. Different navigation criteria should be considered to find the optimal path of the driver. This will help drivers to have different navigation options, which can be the fastest route, the least congested, the least fuel consumption and the least air pollution.

This thesis presents and evaluates a new multi-objective improved simulated annealing Technique for Order Preference by Similarity to Ideal Solution (ISATOP-SIS) algorithm for road congestion avoidance based on an IoV communication

1.3 The Communication Network Congestion Problem

system. The main objective in ISATOPSIS is to provide various route decisions according to different objectives in order to meet the diverse navigation requirements of drivers. For example, the minimum TT, TD, fuel consumption or a trade-off of all conditions. In this thesis, two other algorithms have been implemented: Simulated Annealing Weighted Sum (SAWS) and Simulated Annealing Technique for Order Preference by Similarity to Ideal Solution (SATOPSIS) for compression purposes. The cost function of SAWS has been formulated using the weighted sum method. The cost function of SATOPSIS and ISATOPSIS has been formulated using multi-attribute decision making (MADM) method which is called: Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method [15]. The results of the proposed algorithm ISATOPSIS has been compared with the shortest path Dijkstra algorithm (DA), SAWS and SATOPSIS.

The proposed approach main contribution:

1. ISATOPSIS allows transition from a good solution to a worse solution under a strict condition. This allows the algorithm to find the global optimal solution and avoid becoming stuck in local optimal solutions.
2. ISATOPSIS can work for dynamic path planning by collecting real-time traffic data from IoV and efficiently finding alternative routes for the driver.
3. ISATOPSIS can optimize more than one criteria using the MADM TOPSIS method, which allows alternative routes to be judged on different criteria.
4. ISATOPSIS periodically detects and avoids congestion by selecting the paths that have the minimum traffic, CO_2 emissions, fuel consumption as well as travel time. This is due to combining different navigation attributes in the cost function.

1.3 The Communication Network Congestion Problem

ITSs utilize Vehicular Ad hoc NETWORKS (VANETs) that is the main component of the IoV to broadcast messages between connected vehicles. This helps Traffic Management Systems (TMSs) to control road traffic congestion, which reduces

1. INTRODUCTION

the number of road accidents, decreases travel times, fuel consumption and air pollution.

ITSs have used VANETs for V2V and V2I communication systems. The Wireless Access of Vehicular Environment (WAVE) [16] has been adopted by the Dedicated Short Range Communications (DSRC) community to support V2V and V2I communication systems. WAVE emerged from the IEEE 802.11p and IEEE 609 protocols in the PHYsical layer (PHY) and the Medium Access Control (MAC) layer [17]. This allows the applications in ITS to communicate over short transmission ranges.

VANETs applications can be divided into two types: (i) safety applications that have two kinds of messages: Central Access Messages (CAMs) or beacon messages and Decentralized Environment Notification Messages (DENMs) or event-driven messages [18]. These messages can be transmitted through the Control CHannel (CCH) of the WAVE protocol. (ii) non-safety applications in which messages are sent through the Service CHannel (SCH) for congested road and parking availability notifications.

One of the main problems in VANETs is the congestion in the wireless channel that occurs when many vehicles start to transmit periodically many messages at the same time or relay a large volume of data across the network. This has a consequence that each vehicle transmits at a high data rate without considering the available system resources. This will result in overloading the channel and produces a data congestion problem in the vehicular ad hoc networks. This is due to the limitations of buffer sizes and channel capacity. Therefore, the Quality of Service (QoS) attributes are adversely affected, which affects the network performance and the accurate information is no longer reaching the drivers in a timely manner.

In order to control the transmitted data rates in VANETs, this thesis proposes two approaches based a non-cooperative game approach to formulate the wireless channel congestion problem. In this game, each vehicle is represented as a selfish player and data transmission rates optimized. The proposed approaches are termed Game Theory Approach for Congestion Control (GTACC) and Non-Cooperative Game Approach for Congestion Control (NCGACC).

The main contributions of GTACC are:

1.3 The Communication Network Congestion Problem

1. A new channel congestion mitigation approach is proposed based on non-cooperative game theory to alleviate the data channel congestion in VANET networks. The vehicle sending data rate is characterised by a utility function and the vehicle priorities are formulated as a priority cost function to achieve the desired fairness among vehicles.
2. A utility function for each vehicle is solved using Karush Kuhn Tucker (KKT) conditions and Lagrange multipliers. This gives the optimal data rate for each individual vehicle, which satisfies channel congestion mitigation and provides fair allocation of network resources.

The main contributions of NCGACC are:

1. A new data channel congestion alleviation approach, that is called NCGACC, is proposed. This approach can mitigate the channel congestion by adapting the vehicle data rate based on the vehicles' sending rate, contention delay and priorities which are formulated in the utility function for every vehicle to achieve the desired fairness. Initial work (Game Theory Approach for Congestion Control) was reported in [19], without contention delay being considered in the utility function. As illustrated in the performance evaluation provided in this paper, including the contention delay in the utility function has offered improved performance in terms of QoS parameters.
2. The existence of a unique Nash equilibrium has been proved for the VANET congestion game.
3. The vehicle's utility function is formulated as a constrained non-linear optimization problem. In the initial work, [19], Lagrange multipliers were used to solve the optimization problem. However, the addition of the contention delay in the final proposed utility function means this is no longer appropriate. Instead it is proposed to find the optimal data transmission rates using the Newton-Raphson method for optimization.
4. An extensive performance evaluation is conducted for the proposed approach. This includes testing over both a highway and an urban based scenario. Comparisons are also made with the following algorithms: GTACC,

1. INTRODUCTION

the Network Utility Maximization (NUM) and Non-cooperative Beacon Rate and Awareness Control (NORAC) approaches. The results show that the proposed approach is able to effectively optimize the data transmission rates to alleviate the channel congestion problem.

1.4 Filtering and Predication of the Traffic State

Due to the increasing number of vehicles on the roads traffic state estimation and prediction is an important challenge that has to be addressed. However, modelling the traffic along stretches of motorways/roads is a complex problem with many interacting components and random perturbations [20,21]. For example, consider drivers in a traffic jam. As drivers approaching an incident observe the road traffic congestion forming in front of them, they begin to slow down, resulting in a reduction in speed moving further up the road.

Models of varying levels of detail can be used. Microscopic models [22], deal with the state of individual vehicles, whereas macroscopic models [23–28], consider mean velocities and densities aggregated over time. As a result, macroscopic models are often employed in real time applications [21].

One such macroscopic model for motorways/freeways is the Cell Transmission Model (CTM) [29]. In the CTM a length of road is split into a sequence of links. Each link can then be further separated into segments of road known as cells. The interactions between neighboring cells are then modeled by sending and receiving functions, which along with a maximum number of vehicles allowed in each cell controls the movement of vehicles between cells.

In [20], a flexible Stochastic Compositional Model (SCM) is presented for online modeling of traffic flows. This is an extension of CTM which uses a dynamic equation to describe how traffic speeds evolve in each of the cells. The SCM is flexible in terms of the time update step and cell sizes, which can vary with time if required as long as no single vehicle will miss the subsequent cell during a time step. In this model, the random nature of traffic state evolution can also be explicitly accounted for via probability distributions that govern the sending and receiving functions as well as noise terms.

With such models, it is possible to recursively estimate the traffic states using Kalman Filters (KFs) [30,31]. Alternatively, Particle Filters (PF), [32,33], have

also been successfully applied to traffic estimation problems [21, 22] and shown to be powerful and scalable. In such work past, observations and the system dynamics are used to obtain the conditional distribution of the traffic state. It has been shown that when we do not have measurements available at all of the road segment boundaries that the estimation accuracy can decrease at the boundaries without measurements [21]. This raises the question can we can get an estimate of what these measurements would be in order to improve the overall estimation accuracy of the filter?

Compressive Sensing (CS), [34, 35], and Bayesian Compressive Sensing (BCS), [36], are methods that can be applied to beat the Nyquist sampling rate. It has also been shown that CS based approaches can be used for matrix completion in order to fill in missing data entries [37]. This has been used in a context of the traffic estimation problem [38, 39]. In these works data from probe vehicles is used, i.e. taxis equipped with GPS to give their locations and velocities. However, there is no way to control how many taxis are on the roads or which roads they are on. As a result, the missing data problem for traffic state estimation arises.

In this thesis, we make the assumption that the current traffic state will approach the mean of the historical traffic states from a suitable period of time (unlike for the previous work where the missing data in time and space is directly estimated). As a result, the problem can be formulated as an l_1 norm minimization of the difference between this historical mean and the current traffic state estimate. In order to ensure accurately estimated measurement are achieved a constraint is added to ensure that the estimated traffic state matches the traffic state measurements that are available at given cell boundaries. This can then be further formulated in a Relevance Vector Machine (RVM) type framework, [40], for improved efficiency. Note, the resulting algorithms require the historical measurements (or an estimate of them). As missing measurements are then found they can take the place of the missing measurements in historical data. The resulting CS and BCS based algorithms for estimating the missing measurements are tested with both simulated and real data and integrated with a PF for traffic state estimation.

1.5 Contributions

Our contribution in this thesis includes:

1. A review of numerous road congestion avoidance algorithms and mechanisms that are based on IoV as well as a review of numerous channel congestion control strategies of wireless channel has been presented. Moreover, a review of existing schemes that deal with the traffic state estimation and prediction for real-time free-way traffic simulation.
 - The thesis shows the importance of road congestion avoidance algorithm in providing the driver with optimal path in order to avoid the congestion and achieves the minimum Travel Time (TT), minimum Travel Distance (TD), minimum fuel consumption, minimum amount of emissions or a combination of the four.
 - The thesis discusses and highlights the differences between channel congestion control approaches in IoV and explain how the data congestion in wireless channel degrades the reliability of the network and significantly affects the Quality of Service (QoS) parameters such as packet loss, throughput and average delay. This means the information will be delivered in a timely manner to the drivers, which in turn allows implementation of efficient solutions for improved mobility and comfort in intelligent transportation systems.
 - This thesis shows the importance of traffic state estimation and prediction in decreasing the vehicular traffic congestion on free-way traffic simulation and how the predication is efficient in order to manage the roads and avoid the road traffic congestion.
2. A proposal for a new decentralized approach to avoid the road traffic congestion in the smart cities.
 - a new decentralized multi-objective improved simulated annealing technique for order preference by similarity to ideal solution (ISATOPSIS) algorithm for congestion avoidance based on an IoV communication system has been proposed. The proposed method is tested through

simulation by using a simulation of urban mobility (SUMO) simulator. Simulation results show that ISATOPSIS performs better within congestion avoidance in terms of travel time, path length, fuel consumption and CO_2 emissions as compared to the existing approaches [J1].

3. Two novel wireless channel congestion mitigation approaches are proposed based on non-cooperative game theory to alleviate the data channel congestion in VANET networks.

- To overcome this problem, this thesis proposes a Game Theory Approach for Congestion Control (GTACC) to control the transmission data rates. In this formulation each vehicle is represented as a selfish player. The vehicle sending data rate is characterised by a utility function and the vehicle priorities are formulated as a priority cost function to achieve the desired fairness among vehicles [C1].
- A new data channel congestion alleviation approach, that is called NCGACC, is proposed. This approach can mitigate the channel congestion by adapting the vehicle data rate based on the vehicles' sending rate, contention delay and priorities which are formulated in the utility function for every vehicle to achieve the desired fairness [J3]. Initial work (Game Theory Approach for Congestion Control (GTACC)) was reported in [C1], without contention delay being considered in the utility function.

As illustrated in the performance evaluation provided in this thesis, including the contention delay in the utility function has improved performance in terms of QoS parameters. An extensive performance evaluation is conducted for the proposed approach. This includes testing over both a highway and an urban based scenario. Comparisons are also made with the following algorithms: GTACC, the Network Utility Maximization (NUM) and Non-cooperative Beacon Rate and Awareness Control (NORAC) approaches. The results show that the proposed approach is able to effectively optimize the data transmission rates to alleviate the channel congestion problem.

1. INTRODUCTION

4. A proposal for estimating traffic states within segments of the road using a particle filter and traffic measurements at the segment boundaries.

- In this work an assumption has been made that the current traffic measurements will approximate the mean of the historical measurements from a suitable period of time. This can be assured by formulating the problem as an l_1 norm minimisation which is carried out subject to ensuring the estimates give an acceptable approximation of the available traffic measurements. Then we further formulate the problem in a Bayesian framework, deriving the posterior distributions and the marginal likelihood that are optimised using an RVM type framework. These methods can then be combined with a PF and SCM for improved traffic efficiency. The proposed methods are tested with simulated and real data to verify their effectiveness. We show that it is possible to get accurate estimates of the missing measurements which when used with the PF can give improved accuracy in terms of state estimation accuracy without a significant increase in computation time [C2].

1.6 Thesis Outline

The remainder of this thesis is organised as follows:

Chapter 2 provides a review of related work on traffic detection methods based on VANETs, road traffic congestion avoidance approaches, wireless channel congestion problem strategies and the traffic state estimation and predication in smart cities. First, an overview on why road traffic congestion happens is provided. Then, road traffic congestion detection and avoidance approaches has been discussed. Next, the chapter reviews numerous wireless congestion control approaches and strategies for IoV. Finally, a review of literature works that have been proposed to solve traffic state estimation and predication problem.

Chapter 3 introduces a decentralized multi-objective approach that is called an Improved Simulated Annealing Technique for Order Preference by Similarity

to Ideal Solution (ISATOPSIS) which works efficiently when road traffic congestion occurs by selecting less congested paths for the drivers. The main objective in ISATOPSIS is to provide various route decisions according to different objectives in order to meet the diverse navigation requirements of drivers; for example, the minimum TT, TD, fuel consumption or a trade-off of all conditions.

Chapter 4 presents a new wireless channel congestion control approach in the communication of VANETs has been formulated as a non-cooperative game approach and the vehicles act as players in the game to request a high data rate in a selfish way. Then, the existence of a unique Nash equilibrium is derived. The solution of the optimal game is presented by using Karush-Kuhn-Tucker conditions and Lagrange multipliers. Then, The proposed congestion control approach is tested and evaluated on a highway traffic scenario through simulation and compared with the Carrier-Sense Multiple Access with Collision Avoidance mechanism. Moreover, in this chapter, another cost function has been formulated which is based on the sending rate, contention delay and priorities of vehicles in VANETs. Then, the existence of a unique Nash equilibrium is derived and the solution of the optimal game is presented by using the Newton-Raphson method. Finally, The performance of the proposed strategy is compared with three other algorithms, over two test scenarios: highway and urban traffic scenarios.

This chapter also proposes a new data channel congestion alleviation approach, that is called NCGACC. This approach can mitigate the channel congestion by adapting the vehicle data rate based on the vehicles' sending rate, maximum contention delay and priorities which are formulated in the utility function for every vehicle to achieve the desired fairness. The existence of a unique pure strategy Nash equilibrium has been proved for the VANET channel congestion game. The vehicle's utility function is formulated as a constrained non-linear optimization problem and the Newton-Raphson method has been proposed to find the optimal data transmission rate.

Chapter 5 presents and evaluates road traffic congestion problem using Macroscopic model. First, In this chapter we look at the problem of estimating traffic

1. INTRODUCTION

states within segments of road using a particle filter and traffic measurements at the segment boundaries. When measurements are not available at all of the boundaries the estimation accuracy can decrease. We propose solving this problem by estimating the missing measurements by assuming the current measurements will approach the mean of historical measurements from a suitable time period.

Chapter 6 concludes this thesis and briefly describes some future research directions in the field of congestion control toward the Internet of Things.

1.7 List of Publications

The following publications have emanated from the work of this research:

Peer Reviewed Journal Papers

[J1] Amer, H., Salman, N., Hawes, M., Chaqfeh, M., Mihaylova, L. and Mayfield, M. (2016). An improved simulated annealing technique for enhanced mobility in smart cities. *Sensors*, 16(7), 1013.

[J2] Amer, H. M., Al-Kashoash, H., Hawes, M., Chaqfeh, M., Kemp, A. and Mihaylova, L. (2019). Centralized simulated annealing for alleviating vehicular congestion in smart cities. *Technological Forecasting and Social Change*. 142, pp.235-248.

<https://doi.org/10.1016/j.techfore.2018.09.013>

Peer Reviewed Conference Papers

[C1] Amer, H. M., Tsotskas, C., Hawes, M., Franco, P. and Mihaylova, L. (2017, October). A game theory approach for congestion control in vehicular ad hoc networks. *Proceeding of the IEEE Sensor Data Fusion: Trends, Solutions, Applications (SDF)*, 2017 (pp. 1-6).

[C2] Hawes, M., Amer, H. M. and Mihaylova, L. (2016, August). Traffic state estimation via a particle filter with compressive sensing and historical traffic data. *Proceeding of the 19th International Conference on Information Fusion (FUSION)*, August 2016, pp.1–8.

[C3] Amer, H. M., Al-Kashoash, H. A., Kemp, A., Mihaylova, L. and Mayfield, M. (2018, July). Coalition Game for Emergency Vehicles Re-Routing in Smart Cities. *Proceeding of 10th IEEE Sensor Array and Multichannel Signal Processing Workshop (SAM)*, 2018 (pp. 306-310).

Under Review Journal Papers

[J3] Amer, H. M., Al-Kashoash, H., Hawes, M., Mayfield, M. and Mihaylova, L. (2018). Non-Cooperative Game Based Congestion Control for Data Rate Optimization in Vehicular Ad Hoc Networks. Submitted to Elsevier Ad hoc Networks, 2019.

Co-Authored Publications

[J4] Al-Kashoash, H. A., Amer, H. M., Mihaylova, L. and Kemp, A. H. (2017). Optimization-Based Hybrid Congestion Alleviation for 6LoWPAN Networks. *IEEE Internet of Things Journal*, 4(6), 2070-2081.

[C4] Hawes, M., Amer, H., & Mihaylova, L. S. (2017, August). Traffic state estimation via a particle filter over a reduced measurement space. *Proceeding of IEEE 20th International Conference on Information Fusion (Fusion)*, August 2017, pp 1-8.

1. INTRODUCTION

Chapter 2

Background and Literature Review

2.1 Mathematical Background

2.1.1 The Simulated Annealing Approach

Simulated annealing is an optimization algorithm [41] that simulates the process of annealing metallurgy. Simulated annealing allows transference from a given state to a worse state under specific situations. This gives the algorithm an opportunity to jump out of local minima or maxima and move toward the global optima.

Simulated annealing starts with a set of randomly-chosen solutions. Each iteration produces a new solution of state vectors based on the prior solution. Each vector in the current solution gives rise to a vector in the next solution. For a given state vector, a new solution is chosen using a random selection method. Let r_i designate the random vector associated with the state vector x_i . The value of the objective function f is computed for the performance value r_i . If $f(r_i)$ is better than cost function $f(x_i)$ of x_i , then r_i replaces x_i in the next generation. Otherwise, compute Δ is the absolute difference value as follows:

$$\Delta = |f(r_i) - f(x_i)| \quad (2.1)$$

Based on this, a probability of transitioning $P(\Delta, T)$ is computed. The function that governing the probability depends on the value of delta Δ and the temperature T . One such function is:

$$P(\Delta, T) = e^{-\Delta/T}. \quad (2.2)$$

When the temperature is high, the exponential is near unity for every value of Δ . This gives the state a flexibility in transition from one state to another. As

2. BACKGROUND AND LITERATURE REVIEW

the temperature decreases, the exponential gets closer and closer to zero. This freezes the state in place and only accepts transitions to better states. Normally, the temperature is decreased with each iteration. The simulated annealing method is simple to implement and does not require a large computational overhead to process the algorithm. This makes the algorithm suitable for many optimization problems. Moreover, controlling the temperature parameter in the simulated annealing allows the algorithm to avoid local maxima or minima. This prevents finding a local solution and increases the chance of convergence to the global optimum.

2.1.2 The Multi Attribute Decision Making

Multi-Criteria Decision Making (MCDM) is a discipline that deals with the structuring, finding decision and planning problems including various attributes. The goal is to support decision makers that are dealing with conflicting criteria. Normally, there is no a unique optimal solution for MCDM problems and the best solution is found by evaluating the alternatives and determining the best alternatives between solutions. Decision-making processes include a number of actions to be taken: determine the problems, formulating the preferences, assessing the alternatives, and calculating the best alternatives. In order to solve MCDM problems, the first step is to determine the number of attributes that are existed in the problem (i.e., determine the problems). The attributes or criteria can be divided into two main types: cost and benefit attributes. In the cost attributes, the lower the value is the best such as the travel time. In the benefit attributes the high the value is the best such as travel speed. In the next step, it is required to obtain the suitable information in which decision-makers can accurately reflect and consider the decisions (i.e., formulating the preferences). Then a set of possible alternatives should be implemented in order to ensure that the aim will be attained (i.e., measuring the alternatives). In the final step, we need to choose a proper approach to support us in assessing and ranking the available alternatives (i.e., determining the best alternative). There are several types of MCMD methods such as Analytical Hierarchy Process (AHP), TOPSIS, the Elimination Et Choice Translating REality (ELECTRE), Grey Relational Analysis (GRA), etc.

[35]. A MCDM problem with n alternatives and m attributes can be described by a decision matrix \mathbf{A} as follows:

$$\mathbf{A} = \begin{matrix} & c_1 \dots & c_j \dots & c_m \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} & \begin{bmatrix} r_{11} \dots & r_{1j} \dots & r_{1m} \\ r_{21} \dots & r_{2j} \dots & r_{2m} \\ \vdots & \vdots & \vdots \\ r_{n1} \dots & r_{nj} \dots & r_{nm} \end{bmatrix} \end{matrix} \quad (2.3)$$

where r_{ij} represents the value of j^{th} attribute for the i^{th} alternative and c_j represents the weight of j^{th} attribute for all $i = 1, 2, \dots, n$ and $j = 1, 2, \dots, m$.

2.1.3 The Newton-Raphson Method

The Newton Raphson method finds a way to calculate numerically the zeros of a one-dimensional function over a predetermined range. When the objective function is differentiable, we may take the derivative of the objective function and set it to zero. The Newton Raphson method may be used to determine the zeros of the derivative to numerically find the values of the independent variable that locates the stationary points. The Newton Raphson method starts using some predetermined test point x_0 . This point is the starting point for the algorithm. If we have some knowledge of where the stationary point may be, we choose x_0 in the vicinity. The method will proceed iteratively. We start with an initial point x_0 , then compute the next point x_1 , then compute another point x_2 , etc. The Newton Raphson method is formulated as follows:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}. \quad (2.4)$$

At a stationary point, the derivative must be zero. This method will quickly converge to the stationary point when we are near the stationary point and when the second derivative is nonzero in the vicinity of the stationary point. If the second derivative becomes large, the denominator increases which allows the convergence (the ratio is the correction to the current position, when the ratio is large, there is little change to the current position and the convergence rate decreases).

2. BACKGROUND AND LITERATURE REVIEW

2.1.4 Game Theory Fundamentals

Game theory is a discipline of employed science and utilized mathematics. It has been applied to a diversity of systems such as political science, economics, computer science, philosophy, biology, and recently communication networks [42,43]. Game theory can be categorized into two main sets: non-cooperative and cooperative. If there is no communication or negotiation among the players and they choose strategies individually from each other, then the game is non-cooperative, contrarily, it is cooperative [42]. Hither, the concentration of this thesis is on non-cooperative game theory. The non-cooperative game theory has the ability to concentrate on the analysis and study of competitive decision-making including various players. It gives an analytic model convenient for describing the communications and decision-making operation including different opponents with relatively or entirely contrasting concerns over the result of a determination manner which is affected by their operations. This approach does not require the players to have knowledge about each other strategies as in cooperative approach. It involves three main elements: a group of players, strategies set and utility functions. The non-cooperative game theory can be formulated as follows [42]:

Definition 2.1.1 *A strategic non-cooperative game can be represented in form of a triplet $G = (N, (S_i)_{i \in N}, (\Phi_i)_{i \in N})$, where:*

- N is a group of players, i.e., $N = \{1, \dots, N\}$.
- S_i represents the possible strategies for every player i .
- $\Phi_i : SS \rightarrow \mathbb{R}$ is the utility function for player i , with $SS = \prod_{k=1}^m S_k$ (Cartesian product of the strategy sets).

A player chooses a strategy with 100% certain, this strategy is called as ‘pure strategy’. In contrast, a player could choose every strategy with a particular probability. This concept is known as a ‘mixed strategy’. A non-cooperative game problem can be solved by applying different solutions such as the best response or the Nash Equilibrium that is considered as the most common solution presented by John Nash. Nash Equilibrium provides an optimal solution for all players of the game when no player can improve its profit by adjusting the current strategy. The Nash Equilibrium is described as follows [44]:

Definition 2.1.2 *A pure-strategy Nash equilibrium of a non-cooperative game $G = (N, (S_i)_{i \in N}, (\Phi_i)_{i \in M})$ is a strategy profile $\mathbf{s}^* \in SS$ such that $\forall i \in N$ we have the following:*

$$\Phi(s_i^*, s_{-i}^*) \geq \Phi(s_i, s_{-i}^*), \quad (2.5)$$

$\forall s_i^, s_i \in S_i, s_i^* \neq s_i, \forall i \in N$ where s_{-i}^* is strategies vector of all players except player i .*

2.1.5 Compressive Sensing and Bayesian Compressive Sensing

CS is the science of reconstructing signals or images from sensed data. This method has been applied to various practical problems of the computer technologies. In CS, the dilemma decreases to determining a linear system of equations once the process of the data retrieval is linear. For example, if $\mathbf{y} \in C^m$ represents the observed data and it is linked to the signal $\mathbf{x} \in C^N$. Then, the mathematical expression of the CS is as follows:

$$\mathbf{Ax} = \mathbf{y} \quad (2.6)$$

where $\mathbf{A} \in C^{m \times N}$ is a matrix that models the process of information or the linear measurements. Then, by solving the linear expression above the x can be reconstructed. The conventional knowledge recommends that the amount of estimated information must be at least as large as the signal length N (the number of components of x). This theory is the foundation for the largest machines used in the modern technology, such as imaging of medical systems, analog-to-digital conversion, mobile communication and radar. The principle of CS that is if $m < N$ then the linear equation in (2.6) indicates that the system under indefinite solutions. Therefore, the assumption of additional information or the knowledge of the image or signal is required because it is very difficult to retrieve \mathbf{x} from \mathbf{y} in the situation of $m < N$. Therefore, by using certain assumption or knowledge the signal or image can be reconstructed when the quantity of estimated data is smaller than the image size. This phenomenon is known as a compressive sensing, compressed sensing, compressive sampling, or sparse recovery [45].

2.2 Challenges in Intelligence Transportation Systems

Road traffic congestions are created by many causes: some are foreseeable such as road limited capacity, peak hour, unplanned signalling and bottlenecks and others are unforeseeable due to the traffic accidents, weather situations, and human behaviour. This has produced a vital financial and productivity damages, affecting the development of the flow of vehicles and make it a key challenge within smart cities. Determining such a dilemma can be supported by data collected through sensors spread as an element of smart city initiatives, which then have to be transmitted to vehicles/drivers to enable them to make a choice with regards to alternative routes. Therefore, the ITSs uses the IoV in order to broadcast messages among the drivers which contain information regards to the traffic state. This could help to improve traffic mobility and reduces traffic congestion. However, collecting a large amount of data via the deployed sensors or broadcasting many messages through the limited wireless channel capacity could lead to a data channel congestion problem which effects on the network performance and reduces the accuracy of the transmitted information due to a high probability of missing information. Therefore, the traffic state estimation with spares measurements can be considered as a big challenge which helps to estimate the missing information and increases the accuracy of the traffic prediction. This chapter is presented a detail literature review about the congestion problem of vehicular traffic flow and IoV wireless channel in smart cities. Also, the traffic congestion detection approaches, notification schemes of the traffic congestion and traffic flow estimation and predication approaches are given in this chapter.

2.3 Route Selection to Avoid Vehicular Traffic Congestion via Multi-Objective Optimization

Numerous methods and different algorithms have been proposed to solve the problem of road traffic congestion in the smart cities by using IoV concept. In this section, a discussion and review of these methods and algorithms are given.

2.3 Route Selection to Avoid Vehicular Traffic Congestion via Multi-Objective Optimization

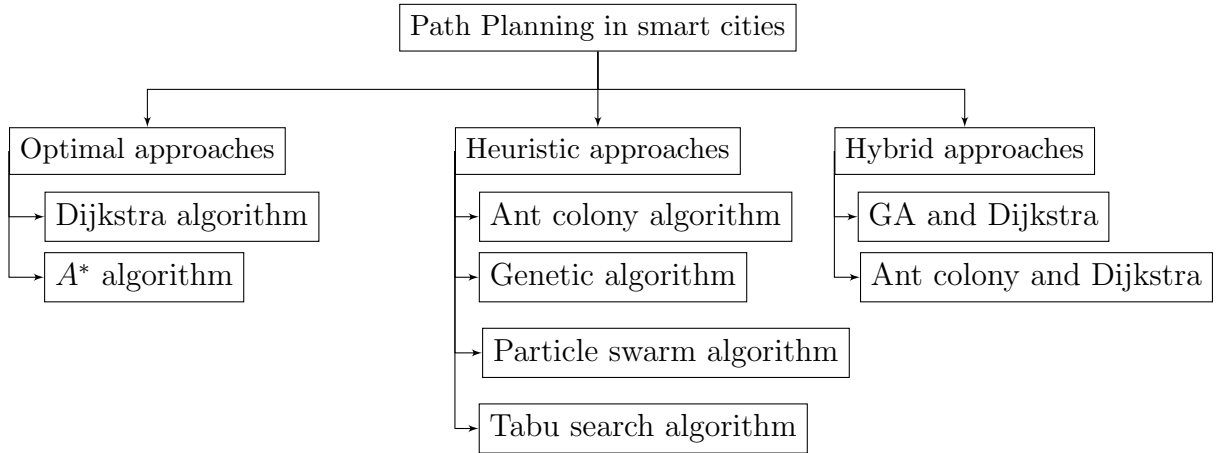


Figure 2.1: Taxonomy of traffic congestion avoidance in smart cities.

2.3.1 Traffic Congestion Avoidance Routing Approaches

Numerous studies have been published on IoV as part of IoT to find a solution to the traffic congestion problem in order to reduce the TD, TT and fuel consumption. In this section, a discussion and review of these routing algorithms is given. The algorithm aims to send Geo broadcast messages in V2V and V2I communications [46]. The algorithm has used an event-driven message instead of a beacon message sent periodically. This message is transmitted to all vehicles which are within a specific range to provide the driver with information about traffic conditions. However, this approach focuses only on providing information to other vehicles without any mechanism to avoid the congested area.

A new Dijkstra algorithm has been proposed in [47]. This algorithm encompasses new inputs for vehicle path planning, along with a reactive planner to update the selected path according to the required route changes. A general classification of vehicle routing algorithms and evaluation metrics in smart cities is also presented. Figure 2.1 shows the classification of most relevant vehicle routing algorithms based on VANETs. However, this is done without any performance evaluation.

In [48], the authors evaluate four algorithms: static Dijkstra, static A*, dynamic Dijkstra and dynamic A*. The evaluated algorithms have been applied in three different test scenarios (city centre, suburban and rural). According to the performance evaluation, the authors recommend that the A* based algorithms are the best routing algorithms in the differing road environments. However, the

2. BACKGROUND AND LITERATURE REVIEW

drawback of these algorithms is that they utilize only a single objective when finding the alternative paths, which leads to the transfer of the congestion to other roads.

In [49], the authors propose an algorithm called: a Cooperative Traffic congestion detection (CoTEC), that uses fuzzy logic control with two inputs (the speed and the density of vehicles) and one output (congestion level). This algorithm uses Cooperative Awareness Messages (CAM) or beacon messages, sent periodically to other vehicles telling them to avoid the congested area. In addition, it detects the congestion by using an external metric called the level of service (LOS) developed by Skycomp. This involves the classification of congestion levels from aerial surveys of highways. Once obtained this information is then combined with data from organizations such as local authorities. As a result, the performance of the algorithm is heavily dependent on the accuracy of the data from these external organizations. Additionally, no mechanism is provided for drivers to find the optimal route for their journey.

In [50], a centralized framework is proposed to obtain real-time coordinates of vehicles and their direction and velocity, which can be used to determine traffic congestion levels. When congestion is detected, vehicles close by are re-routed using two algorithms. The first algorithm, Dynamic Shortest Path (DSP), allocates to each vehicle the shortest path (smallest TT) to reach their destination. However, the drawback of the first algorithm is the probability of transferring the congestion to other areas. Therefore, the second algorithm, random multipath K shortest paths (RKSP), determines the K shortest paths for each vehicle and randomly allocates the vehicle to one of them. As a result, of using K alternative paths it is possible to ensure the congestion is not just transferred to a different road. However, the drawback of this algorithm is that the choice of routes is arbitrary and uses a single objective function.

In [51], the authors propose an Ant-based Congestion Avoidance System (ACAS). ACAS integrates the average travel speed prediction with segmentation of a city map to detect and reduce the congestion. It collects the traffic information from V2V communications and RSU to forecast the average speed of the roads. Then it uses a weighted sum method to formulate the cost function for the roads, where the weights have been calculated by trial and error. However,

2.3 Route Selection to Avoid Vehicular Traffic Congestion via Multi-Objective Optimization

this algorithm still chooses the shortest paths when re-routing the vehicles to avoid the congestion. As a result, this transfers the congestion to a new road.

In [52], the authors describe a distributed real-time V2V congestion evasion technique. Congestion levels are detected and vehicles re-routed using congestion messages called request/receive messages (instead of beacon messages). When a vehicle reaches an intersection and can select from different paths, it sends a congestion request packet to all neighboring vehicles within its communication range to obtain the traffic status information. This message encompasses a list of roads that form potential paths to their destination. The vehicle will select its next potential route based on the received traffic data. A congestion response message is transmitted only when a congestion request is received. If the congestion request message is received twice the vehicle will not send a response message and the congestion message will be discarded from the database of the receiving vehicle. This ensures that no redundant information is transmitted. Otherwise, the vehicle will broadcast the response message, which includes data about the congested roads available at the receiver. The vehicle that receives the congestion message request will select the road that has the minimum travel time. However, this method has two drawbacks. Firstly, it includes a high delay time due to sending the traffic data. Secondly, the authors have not considered the high probability and consequences of lost packets in a built up area.

In [53], the authors suggest an ITS based on RSUs in order to avoid traffic congestion. This system is triggered only when an accident occurs. The vehicles involved start to transmit alert messages with the location of the accident to the other vehicles within their transmission range. Every vehicle that has received an alert message checks if they are near an affected area. If they are far from the accident point, the vehicle will delete the received message. However, if the vehicle is near to the accident point, it checks its route to establish whether it is affected by the accident or not. At this stage, a new route can be calculated and assigned to the vehicle. However, the drawback of this method is that the re-routing is done based on either a static DA or A* algorithm. This would transfer the congestion from one area to another. In addition, this system does not consider the traffic congestion that occurs due to the high vehicle densities in a given area.

Recently, in [54, 55], the authors propose two systems called: a Geographical Accident Aware of Reducing Urban Congestion (GAARUC) and a solution

2. BACKGROUND AND LITERATURE REVIEW

using cooperative re-routing to prevent congestion and improve traffic condition (SCORPION) based on the ITS and IoV. The GAARUC is decentralized system and it offers a new path to the drivers considering all cars and available routes in the region nearest to an accident. The SCORPION is a centralized system that collects the traffic data from RSU and it uses the concept of fuzzy logic to predict congested roads. However, both systems propose the re-routing based on static Dijkstra or A* algorithms and thus will have the same shortcoming as in [48], i.e. the possibility of moving congestion to a new area.

Other studies have reviewed the most relevant algorithms to calculate the route in the Vehicle Route Problem (VRP) such as in [7–9, 11, 56]. In [56], a modified version of ACO is proposed in order to reduce the travel time for vehicles on the move. The Modified Ant Colony Optimization (MACO) is a variation of the classical ACO in which the idea of an ant colony has been reversed. Instead of, attracting the vehicles toward roads which have high pheromone levels, the MACO algorithm routes and disperses the traffic toward paths with lower pheromone values to avoid the congestion. However, the cost function of this algorithm is very similar to the classical Dijkstra algorithm.

In this thesis, a novel dynamic multi-objective optimization algorithm is developed, which combines Simulated Annealing (SA) with the MADM TOPSIS cost function to provide the driver with optimal paths. In addition, the proposed algorithm utilizes real-time data using IoV, unlike other works where the static DA or A* is used to re-route the vehicles and leads to transfer of congestion onto other roads. Our proposed approach is also better than the ACO based methods as the ACO can become stuck in local optima solutions (rather than the global solution). This is because of the ACO updating the pheromone based on the current optimal route [57].

2.3.2 Road Traffic Congestion Detection via IoV

ITSs uses IoV to sent traffic information between connected vehicles. This provides a good monitoring system and helps to improve the traffic flow on smart cities. The WAVE is an approved adaptation to the IEEE 802.11 that is used to support the IoV applications in short range communication [58]. With the equipment installed in the vehicles themselves on-board unit or on the road RSU, the WAVE protocol supplies the real-time traffic information to improve the safety,

2.3 Route Selection to Avoid Vehicular Traffic Congestion via Multi-Objective Optimization

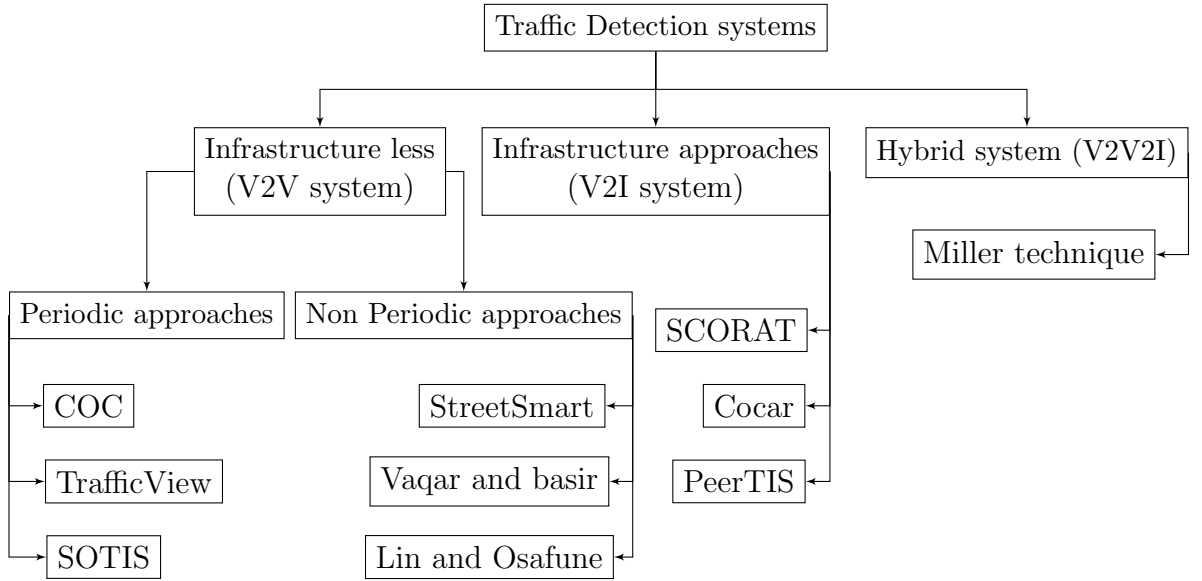


Figure 2.2: Taxonomy of traffic congestion detection systems based on VANETs.

convenience and reduce the traffic congestion of the transportation. The WAVE IEEE 802.11p standard emerges from the allocation of the Dedicated Short Range Communication (DSRC) spectrum band in the United States and the work done to define the technology to be used in this band.

Some studies have investigated the performance and the range that WAVE protocol can coverage in urban environments and they have found that the WAVE can coverage from 300 to 1000 metres [59,60]. Additionally, various types of communication transmission can be used in vehicular networks [61]: Unicast communication, in which data are transmitted from a source node to a destination node through multiple-hop wireless communication, Multicast/Geocast communication, wherein both information are transmitted from a source to many destination nodes with a contrast that in geo cast communication the destination nodes associated by geographic positions, and Broadcast communication, where the source transmits information to all its neighbours.

The traffic flow efficiency and congestion reduction can be achieved by utilising the real-time information from VANETs. According to the Traffic Information System (TIS) [49], traffic congestion detection approaches that are used a microscopic model can be classified into three main parts: V2V, infrastructure based (V2I system) and Hybrid (V2V2I system) approach. Figure 2.2 shows the taxonomy of traffic congestion detection systems based on VANETs.

2. BACKGROUND AND LITERATURE REVIEW

Vehicle to Vehicle Communication Approaches

This system is decentralized approach and it depends mainly on V2V communication. This system allows vehicles to send and receive the traffic information between each other via multi-hop communication. V2V system is very powerful and scalable when it applied to safety applications due to rapid detection of collision or congestion on the city roads. The main advantage of this system is that the less time delay as compared with the V2I system and it is very efficient for congestion detection/avoidance mechanisms. Moreover, this system does not require a high number of sensors to be deployed on city roads which make it much cheaper than V2I structure. The V2V system can be classified into two technique: non-periodic and periodic traffic data messages.

1. Non-periodic techniques A StreetSmart technique is presented in [62] to estimate the traffic states. This system does not employ a periodic transmission of information on every road among vehicles. In this system, only small number of vehicles participate in the transmission of traffic data. This system also does not require a fully connected network. Every vehicle records its speed and local traffic map. Then, the speed maps are exchanged between vehicles that are close to each other and a cluster approach is used to aggregate the traffic data. The method is evaluated using a simulator developed by the author. The result shows that the StreetSmart system can decrease the network overhead by limiting the periodic transfer of traffic data to only situations of unforeseeable or irregular traffic states.

Vaqar and basir system is proposed in [63]. The data is collected via a vehicle in vehicular ad hoc network. Then, this data is depicted as a snapshot in time of the current traffic state of the road segment. This snapshot of the current traffic state is treated as a pattern in time. Then, these patterns are evaluated via pattern recognition method called: A weight-of-evidence-based classification. This method is employed to analyse various road traffic segments. The data is generated using microscope traffic model to evaluate various levels of a vehicle provided with communication ability. However, this method contains a high delay time to justify the traffic state estimation which leads to unreliable road congestion detection.

2.3 Route Selection to Avoid Vehicular Traffic Congestion via Multi-Objective Optimization

Lin and Osafune technique is presented in [64]. It relies on the collected information from the V2V system to estimate the traffic states. The present procedure identifies with the strategy and device for distinguishing and diffusing information of traffic conditions via disseminated V2V communication framework. This framework is accomplished by the technique and device assembly as per the present development as characterised by the free claims. The current procedure suggests a WSN system, for example, wireless V2V communication by which traffic states can be resolved. The traffic state data that can be calculated are a free flow of traffic, traffic congestion and complete freeze and/or limited traffic flow. This method makes decision methodology so that neighboring vehicles transfer their traffic state and try to achieve a general vote.

2. Periodic techniques In this system, the traffic state information is transferred between vehicles using periodic beacon messages.

Contents oriented communication (COC) system is presented in [65]. In this system, every vehicle utilises the road traffic density from received beacon messages and after a further process, this information is transmitted to other vehicles. As a result, a vehicle obtains traffic density information for different locations and detect congestion levels by comparing the road traffic density estimated with average traffic density values for the road segment. Vehicles can identify the congested region from real-time information. However, the proposed solution can cause network overhead due to periodic conveying of traffic data.

In [66], a TrafficView system is proposed. This system aims to collect and disseminate the traffic data such as speed and position of vehicles. It allows vehicles to view and evaluate traffic state in ahead of them. The transmission of information is very restricted to the position of vehicles in front of current vehicles. After a further process of received data, a report is transmitted via a single message by vehicles to others they know about them or they are in their transmission range. Once vehicles receive a new message, they update their local information and send the updated report in the next transmission period. This system uses an aggregated method in order to accumulate traffic information in a single packet. The proposed system suffers from

2. BACKGROUND AND LITERATURE REVIEW

network overhead and does not have a mechanism to choose the vehicle that will be responsible for broadcasting the traffic data related to the traffic states.

A self-organizing traffic information system (SOTIS) is presented in [67]. This system is restricted to an approximate area of 50 to 100 km. In SOTIS, each vehicle monitors local traffic state via beacon messages that are periodically received from other vehicles. After a further process, the resulted traffic information then transmitted to all neighbored vehicles. Additionally, the roads are divided into different size of segments and the data is sent on per segment. The length of each segment relies on its distance from the sending vehicle. Each vehicle maintains a database called knowledge base (KB) to store obtained traffic information for each segment of the road. This system depends on the selecting of cluster head that usually creates an overhead of the network. Moreover, the partitioning of the road segment is very complex and not a trivial task.

Vehicle to Infrastructure Approaches

There are many systems and approaches have been employed V2I system or RSU such as SCORAT [68], TrafficCon system [69], PeerTIS system [70] and Cocar system [71]. Most of these systems are based on a centralised architecture such as traffic management centre (TMC) in which the real-time traffic information are received and processed by the roads network via sensing devices (e.g WSN, cameras, induction loop, mobile phones, mobile phone masts, ...) that are monitor the traffic density. The resulted data then transmitted to the road user applications such as cellular phones in order to utilise them and have a view on the congested area. However, these systems are suffered from two drawbacks. The first drawback is that the implementation of such systems is very expensive because it requires deployments of large numbers of sensor throughout almost all the city roads in order to efficiently monitor and estimate the traffic state. The second drawback is that when the centralised centre has failed the entire system are exposed to fail. Moreover, these systems require a high delay time to process the traffic data due to send all the traffic information to a central unit.

Hybrid Approaches

Both V2V and V2I systems have been integrated to form a hybrid system called (V2V2I) in [72]. This system has taken the advantage of both systems the fast response of V2I and the distributed architecture of V2V. In Miller approach, the transportation area is divided into zones and in each zone, only one vehicle is selected to be a super vehicle or a cluster head. This super vehicle is only capable of communicating with the RSU or other super vehicles. The other vehicles only can communicate with the cluster head (super vehicle) that is responsible for the zone in which they are currently traversing. However, this system suffers from additional network overhead due to the selecting of a super vehicle.

2.4 Game Theoretic Approaches to Resolving Congestion in The Communication Network

Numerous strategies have been published on the channel congestion control problem in VANETs. They include power adaptive strategies, data rate adaptive strategies [73], Carrier-Sense Multiple Access with Collision Avoidance (CSMA/CA) parameters adaptive strategies [74], prioritizing and scheduling approaches [75], and hybrid strategies [76]. However, the focus of this thesis is on dynamic data rate adaptation approaches due to the significant influence of data rate adaptation on controlling the channel loads and congestion avoidance in the communication network. Adapting the data rate is critical because high data rate causes to channel congestion while low data rates result in inaccurate traffic information being communicated between drivers. Figure 2.3 describes a taxonomy of the strategies that have been utilized to alleviate the congestion problem in VANETs.

2.4.1 Adaptation via Data Rate

1. Periodic Messages Adjustment

- **Adaptation based on vehicle parameters:** Beacon adaptation approaches have been proposed in [77] and [78]. In [77] the number of road lanes has been utilized in the beacon adjustment approach. The data transmission rate of the vehicles is decreased once they are driving

2. BACKGROUND AND LITERATURE REVIEW

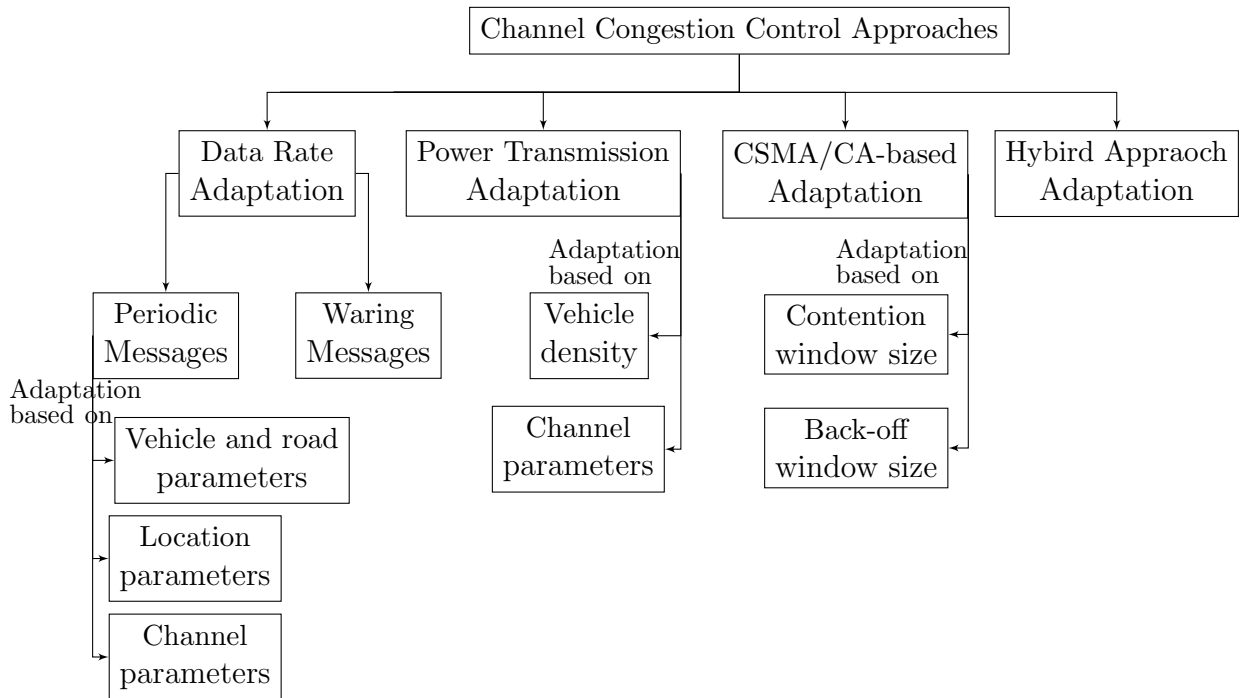


Figure 2.3: Taxonomy of adaptive safety messages approaches

on roads with multiple lanes. However, this approach has a drawback in that it changes the data rate according to the number of lanes only, rather than considering an accurate measure of the actual traffic densities on the roads. Another beacon adaptation strategy has been proposed in [78]. This approach has considered several performance criteria such as vehicles direction, density and road status in order to check the effect on the transmission frequency. Nevertheless, the proposed solution has not studied the effect of combining these attributes into one cost function in order to obtain the optimized data rates. Furthermore, the unfair reduction of beacon frequency affects the safety message that required to be communicated amongst vehicles to share the traffic data.

In [79] the data rate of non-safety applications has been adopted by using the Utility-Based Packet Forwarding and Congestion Control (UBPFCC) strategy in order to control the channel congestion. This strategy utilizes the messages size and a specific cost function to adapt the data rate. The UBPFCC strategy estimates the average cost func-

2.4 Game Theoretic Approaches to Resolving Congestion in The Communication Network

tion value for every vehicle based on its transmitted messages and the remaining data rate to the vehicles. However, this strategy does not consider the road traffic density or the vehicles' behavior when calculating the average utility of the vehicles. This means vehicles with high-cost function value will reserve a large amount of the data rate while low utility vehicles forced to freeze their transmitting messages once the wireless channel is congested. Moreover, this strategy may still lead to an overload of the wireless channel due to exchanging the available data rate between vehicles while neglecting the traffic density and congestion of the vehicles.

An Adaptation Beacon Rate (ABR) approach has proposed in [80] which is based on fuzzy logic control in order to minimize the beacon rate. In this approach, the percentage of vehicles driving in the same direction and traffic condition of vehicles have been considered as inputs to the fuzzy logic control in order to obtain the optimal data rate. However, this approach has not considered the emergency messages that are generated due to the occurrence of events or hazardous situations. This still leads to the congestion in the control channel and adversely affects the QoS of the network.

In [81], the authors have proposed a Fair Adaptive Beaconing Rate for Inter-vehicular Communications (FABRIC) algorithm. The Network Utility Maximization (NUM) problem has been used to model the sending rate of vehicles in the network. Moreover, the scaled gradient projection algorithm has been used to solve the dual of the NUM problem and find the optimal data rate for each vehicle. However, this approach has not considered the emergency events and messages priorities.

- **Adaptation based on location and position parameters:** A data rate adaptation approach that is called On-Demand Data Control has been proposed in [82]. This approach adapts the data rate of periodic packets by utilizing the movement and density of the vehicle on the roads. In this approach, the transmission probability has been calculated based on the errors on the position of the vehicles. In this

2. BACKGROUND AND LITERATURE REVIEW

approach, the transmission frequency increases once vehicles have unexpected movements. Once the channel faces congestion situations, the transmission frequency is decreased to decrease the probability of lost packets. However, the generated event-driven messages in hazard conditions have not been examined in this approach which increases a congestion in the wireless channel.

An improved neighbor localization approach has been proposed in [83]. This approach utilizes the predicted positions of neighbor's vehicles in order to adapt the data rate. This approach uses vehicle's current position and additional information from the received beacon such as vehicle's previous position, direction and speed to predict the position of a neighbor vehicle. A threshold value has been established for each vehicle by estimating periodically the difference among the neighbor vehicles predicted and actual locations. Therefore, if the installed threshold value is less than the error between the predicted and actual location, a new message will be transmitted. Otherwise, the new message will have to wait for the transmission if the error is greater than the threshold value.

- **Adaptation based on channel parameters:** An Adaptive Traffic Beacon (ATB) approach has been proposed in [84]. This approach tunes the beacon frequency in order to decrease the load on the VANETs channel. The ATB is a dynamic and decentralized approach that adjusts the beacon frequency by utilizing the weight of messages and the channel status. This approach has used the network limitation, the Signal to Noise Ratio (SNR) and the neighboring vehicles to calculate the channel status. The importance of every packet is calculated based on the vehicles distance, the positions of present events happening on the roads of the city and the lifetime of the message. However, The ATB strategy does not meet the MAC layer requirements. This is because it is only calculated beacon receiving probabilities. Moreover, the ATB strategy leads to a lack of disseminated safety messages between drivers due to the inequitable decreasing of the beacon message frequency.

2.4 Game Theoretic Approaches to Resolving Congestion in The Communication Network

An adaptive data rate scheme has been presented in [85] which is called Periodically Updated Load Sensitive Adaptive data Rate (PULSAR) in order to control the congestion problem in VANETs. In the PULSAR scheme, the data frequency is adapted based on three main stages. In the initial stage, the bottleneck detection is started by measuring the Channel Busy Ratio (CBR). Once the CBR grows larger than the pre-defined threshold, the next stage is started. Then, the data frequency is tuned to decrease the load on the channel. However, the data frequency increases gradually, if the CBR is less than the specified threshold. In the last stage, the vehicle that selected the data frequency broadcasts it to the other drivers that are in the shared communication range. Unfortunately, when using this approach channel congestion can still occur. This is because safety application approaches have not been considered. Moreover, the additional exchange of the congestion information between vehicles leads to an extra load on the channel.

2. **Warning Messages Adaptation:** The authors in [86], proposed a cross-layer congestion control approach that decreases the data rate of the periodic beacon packets as compared to the emergency messages. In order to detect the congestion, the channel occupancy time is estimated and compared with a specified threshold value. Once the congestion is detected, the application layer is triggered by the MAC layer to freeze all the beacon messages and the control channel is maintained only for the event-driven messages. Then a notification message is sent by the first blocking vehicle to all its neighbours to inform them to use the MAC blocking and freeze the data rate of beacon messages. However, freezing the beacon messages leads to a reduction in the amount of information on positions being shared between vehicles. Moreover, the requirements of safety applications messages have not been considered in this approach.

However, the above mentioned approaches still suffer from common drawbacks. These are channel overloading caused by exchanging additional information, unfair reduction of beacon rates and beacon messages being discarded. This affects the quality of the information provided to individual vehicles. Additionally, they have not considered event-driven messages that

2. BACKGROUND AND LITERATURE REVIEW

can also contribute to further channel congestion. To overcome these issues, this thesis proposes the NCGACC to control the transmission data rates. In this formulation, each vehicle is represented as a selfish player.

2.4.2 Adaptation via Power Transmission

The power adaptation strategies mean the vehicles transmission range is tuned to reduce the data congestion in the channel. The transmission power adaptation in VANETs is critical because the opportunity to communicate with neighbouring nodes is minimized and the fairness in VANETs cannot be guaranteed. It is very important to send the safety information at the maximum transmission range in order to reach further regions of the road network. However, a high transmission power leads to increase the channel congestion. In order to alleviate the congestion in the wireless channel, the transmission power is adjusted based on different vehicle or channel parameters such as traffic situations, network condition and type of disseminated information.

- **Adaptation based on vehicle density:** Torrent Moreno et al. [87] presented a new strategy that is called Fair Power Adjustment for Vehicular environment (FPAV). The proposed approach increases the likelihood of receiving packets in neighboring vehicles and provides fairness in the system for sharing bandwidth between vehicles. FPAV approach decreases the congestion by controlling the transmission power of safety messages containing beacons and emergency messages. The FPAV algorithm reduces safety messages load by adapting the transmission power based on vehicle density. In this approach, the power range is reduces with increasing of number of vehicles on a road segment. Moreover, this strategy maintains a portion of the data rate for the warning packets. However, maintaining a part of the data rate might decrease the bandwidth in the several circumstances of VANETs.

The authors in [88] proposed an approach that is called Distributed Fair Power Adjustment for Vehicular networks (D-FPAV). This approach provides an efficient power transmission of warning messages by reducing the beacon loads on wireless channel. This approach specifies high priority of

2.4 Game Theoretic Approaches to Resolving Congestion in The Communication Network

event-driven messages as compared to the beacon messages. D-FPAV decreases wireless channel congestion by reducing the transmission power of beacon messages based on vehicle density while event-driven messages are sent with the maximum transmission power. In D-FPAV, every vehicle sends status information to all other neighboring located in it is her transmission area. Then, the transmission power of the periodic packets is adapted based on the utilized information such that it does not exceed a specific threshold value. Then, this new value of the transmission power is communicated among vehicles located in the same area. However, the D-FPAV approach reduces the likelihood of sending beacon messages to the furthest areas which in turn decrease the opportunity of sharing the traffic information with furthest drivers. This is due to the inequitable decreasing of the transmission power of periodic packets. Furthermore, the additional exchange of the congestion data between nodes leads to an additional pressure on the wireless channel.

- **Adaptation based on channel parameters:** Falah et al. [89] proposed an adaptation power control strategy for detecting and controlling congestion based on channel occupancy. This approach adapts the transmission power to obtain the optimal channel occupancy. In this strategy, the channel occupancy is estimated based on different parameters such as transmission frequency, the size of the Contention Window (CW), the range of transmitted packets and traffic density. This approach has utilized different values of the CW size in order to broadcast the high priority messages as compared to low priority packets.

The authors in [90] presented an approach based on the power transmission adaptation in order to reduce the collision in the channel among transmitted event-driven messages. The transmission power has been adapted based on the road traffic conditions and the previous transmission power from the transmitted vehicle. Then, the newly generated messages are sent with a new adapted power control for short range in order to reduce the channel congestion.

2.4.3 Adaptation via MAC Channel Mechanism

The CSMA/CA is an original collision avoidance approach that is used to monitor and control congestion in WAVE protocol. This method estimates the channel capacity for each node in the MAC layer by modifying the size of the contention window and AIFS. These two parameters are very important to decrease the congestion in the wireless channel. Moreover, the exponential regression mechanism is used in the CSMA/CA strategy to control channel congestion. However, when the messages are sent with the high data rate, the exponential regression mechanism is no more not effective tool due to drop the messages before transmission [91], [92] and [93].

- **Adaptation based on contention window size:** Hsu et al. [94] have presented a CSMA/CA adaptation approach that is called an Adaptable Offset Slot (AOS) to control channel congestion in the Mac layer. Once traffic congestion occurs, the AOS approach dynamically adapts the contention window size based on received information of vehicle density. This means the optimal back-off time is estimated by using a number of adjacent vehicles. This approach utilizes hello messages in order to estimates the vehicle density. Then in the next stage, a new size of the contention window is estimated and linearly increases with the increasing number of vehicles. However, in a high-density network, increasing the size of the contention window increases the delay of receiving the safety messages. Therefore, traffic status information is no longer reach the driver in a timely manner.

Jang et al. [95] has proposed a MAC layer approach in order to detect the congestion in the wireless channel by altering the RTC/CTS mechanism and broadcasting packets to predicts the congestion and number of competitive vehicles. Once the congestion is detected, the size of the contention window is dynamically modified to minimize the number of the collision messages and the channel congestion. This approach tries to reduce congestion by increasing the size of the contention window. However, this leads to increase the delay to disseminate the messages. Moreover, the using of TRC/CTS approach leads to load the channel due to the extra exchange of the information.

- **Adaptation based on back-off window size:** Barradi et al. [96] has introduced a congestion control approach in MAC layer. This approach adopted the ranges of AIFS and back-off window size in order to reduce the congestion on the wireless channel and minimize the delay which guarantees the dissemination of emergency messages over the control channel. This approach utilizes acknowledgment messages to prevent the messages retransmission and ensure the safety messages delivery. However, these acknowledgment messages cause more collisions in high-density environments and this leads to the overload of the wireless channel.

2.4.4 Adaptation via Hybrid Approaches

In hybrid strategies, two or more parameters are utilized to control channel congestion. Combining the transmission rate and power settings, adjust the size of the contention window, prioritizing the messages based on the importance of each one, set priorities and schedules are incorporated to alleviate the saturation and congestion in the wireless channel. [92].

The author in [97] has proposed a hybrid approach that integrates the power transmission and the contention window size of the channel access. In order to modify the transmission range, the power control has been adapted based on the calculation of the vehicular density estimation while the size of the contention window has been adapted based on the rate of instant collision and high-priority messages. Once the channel congestion occurs, each vehicle will examine the local vehicle density from the received beacon messages and the power control will be adopted by utilizing a lookup table that matches the desired transmission range to the corresponding value of transmission power. The contention window size is continuously updated to all access categories based on observed the channel situations of the network. Therefore, this approach does not have a fixed contention window size as in the original mechanism of the WAVE protocol.

The authors in [98] have proposed a hybrid approach that is called A Combined Power and Rate Control (CPRC). This approach measures the channel congestion by adapting the data rate and transmission power based on the number of neighbors in the surrounding region. The vehicle density has been estimated by utilizing the observations of the channel busy time and an extra transmission of local traffic information. Then, if the vehicle density is very high and the channel

2. BACKGROUND AND LITERATURE REVIEW

busy time higher than the threshold value, a new packet generation rate and the maximum transmission power are estimated which will not exceed the threshold value.

A hybrid approach adaptation joins messages sending rate and power control is proposed in [99]. This approach utilizes the traffic information of the vehicles and the tracking accuracy in order to adapt the messages rate and the power control. This approach adjusts the beacon frequency base on the errors from the tracking of the neighbouring vehicles. On the other hand, the power control has been adopted by utilizing the channel busy time. This strategy broadcast the messages when the tracking error exceeds the specified threshold value. Additionally, the transmission range of the safety messages has been restricted by defining the maximum and minimum of the power transmission. The power control has been linearly tuned by estimating the channel capacity. However, in some case, the vehicles are controlling the congestion in the wireless channel without detecting if the channel is in a saturated condition. This is due to that the vehicles utilize the local traffic data without sharing them with the nearby vehicles. Moreover, this approach does not support the transmission priority of the emergency messages.

The authors in [100] have proposed a hybrid beacon approach that adjusts both the data frequency and the power control in order to minimize the congestion in the wireless channel and maintain the channel capacity for the warning packets. This adaptation approach includes three stages. At the first stage, the messages are prioritized based on a static attribute that is the content of the information and on the dynamic attribute which is the emergency condition in order to differentiate the high importance packets. The second stage is initiated once the congestion is detected in the wireless channel. The congestion is detected based on collision frequency occurrence, average waiting time of messages and the average number of received beacon. In the third stage, the data rate and the power transmission are adjusted by utilizing the available bandwidth, collision frequency and alternating situation of 1-hop neighbours, respectively. Finally, the adapted data rate and the power transmission are disseminated to the nearby vehicles in order to utilize the estimated values and minimise the congestion. However, the extra exchange of the information leads to overload the channel and increase the congestion.

2.5 Particle Filtering and Compressive Sensing for State Estimation

Methods and approaches in the state of the art have used the most two common models (Microscopic and Macroscopic traffic simulations) to alleviate the road traffic congestion and to control the traffic flow in order to improve the traffic mobility and efficiency. The traffic state estimation is required to be accurately foreseeable with real-time measurements. The Microscopic models such as (SUMO, VISSIM [101] and MITSIMLab [102]) are often employed in estimating local state of traffic flow such as at congested intersections [103], free-way bottlenecks [104], weaving sections [105], merging and lane changing [106], transportation corridor operations [107] and others.

The Macroscopic traffic simulation models like (METANET [25], CTM [29] or SCM [20, 108]) are often considered the relationship of the flow, mean velocities, and density of the traffic flow over a section of roadway. they describe the traffic flow on an accumulated data over time rather than deal with the state of individual vehicles. As a result, the macroscopic models are often employed to large-scale roadway networks [25] or real-time traffic control to reduce congestion and improve the traffic efficiency [21].

A macroscopic model called CTM is proposed in [29] for highway with one entrance and exit. In CTM, the road is divided into homogeneous portions called links. Each link then divided into a number of cells. The interactions between neighboring cells are then modeled by sending and receiving functions, which along with a maximum number of vehicles permitted in each cell controls the movement of vehicles between cells. The CTM evaluates the traffic flow on the roadway to estimate the dynamics densities of vehicles.

SCM macroscopic model is proposed in [20, 108] that is an extension of CTM. The proposed model evaluates the traffic flow on a free-way to estimate the dynamics variables such as densities of vehicles and average velocity. The SCM depends on the dynamic analysis to depict how the traffic speeds ex-cogitate in each of cells. The SCM is more flexible than CTM in choosing the cells size and the time update step. These can vary with time depending on the availability of real-time measurements and the location of the cells if as long as no individual vehicle will jump over a cell during one time step. In this model, the random

2. BACKGROUND AND LITERATURE REVIEW

nature of the traffic state evaluation can also be represented via probability distribution that governs the sending and receiving function. The SCM model allows predictions of the future cost of traffic state by depending on the availability of accurate estimate of the currents variables (speed and density in each cell).

An Urban Cell Transmission Model (UCTM) has been developed in [109] that explains with adequate certainty the main reasons for the urban traffic delay. This model can be used in a Coordinated Model Predicative Controller (CMPC) such as in [110] to determine what switching time can decrease the delay for all vehicles over a shortest predicted average delay when the signal controller has knowledge about the changing ratios. This is done for each intersection by considering the density of vehicles as measured on all segments joined to the intersection.

There are many works have been applied to the above two models to estimate the traffic state. In [111–113], A recursive traffic state estimation is employed using the Kalman filter or Extended Kalman Filter (EKF). The EKF is applied to estimate the unknown variable of the traffic state. These type of filter has been evaluated on a highway. Each lane is segmented into 18 links, each link with the length of 500 meters. These estimators have the benefits and the drawbacks of the Kalman filter: it is computationally cheap but it depends on the assumption that noises obey Gaussian distribution. Additionally, they depend on the linearization of the state and observation function. However, traffic flow can be randomly perturbations, which is characterised by highly nonlinear behaviour. Therefore, the Kalman filter and EKF can rise issues and the accurate of results might be unstable when applied to the traffic state estimation.

The mixture Kalman filter algorithm based on CTM is proposed in [114]. The model only evaluates the vehicles densities and to distinguish between free-flow mode and congestion mode at unmeasured cells on a roadway section. The sequential Monte Carlo method is utilised to nearly deal with the difficulties of inference on a swapping state function with measurement function.

The Unscented Kalman Filter (UKF) algorithm is proposed in [115–117]. The UKF is a method to approximate the first two conditional moments of the state: the mean and covariance. The UKF does not require calculation of Jacobians and Hessians as EKF, which for the traffic state estimation with interconnected components is quite complex. The sigma points are applied to determine the mean and covariance. The UKF estimation is more accurate and easy to implement than

2.5 Particle Filtering and Compressive Sensing for State Estimation

EKF. However, the UKF can suffer from conditioned problem of the covariance matrix. The UKF needs methods for enhancing the numerical properties such as singular value decomposition to overcome this numerical instability.

Recently, only a few number of researchers have discussed the traffic state estimation using particle filter (PF) algorithm. This algorithm does not suffer from the previous drawbacks of the EKF or UKF. This algorithm is a powerful and scalable solution to the non-linear problem and non-Gaussian filtering problem [118]. The idea of PF is that it approximates the posterior probability density function (PDF) at the state model by representing the PDF with the set of particles or samples and each of samples is associated with weight. The estimation can be computed as the expected value of the discrete PDF [119,120]. PF allows to cope with uncertainties and non-linearities of any kind and hence is suitable for the traffic state estimation problem.

The PF algorithm based on SCM model is proposed in [121,122]. Both the densities and average velocity of vehicles have been estimated. The proposed method has been investigated based on real traffic data from Belgium roadway. A parallel PF algorithm with the Gaussian sum PFs for Large-scale traffic systems has been proposed by [123] to deal with the difficulty of collecting high amounts of heterogeneous data from different types of sensors. Other studies have been tested in other countries for example in [124] PF algorithm based on METANET model has been investigated based on real traffic data from Beijing's freeway. The filter is investigated on the roadway with the one ramp on and ramp off meter at each cell. The PF aims to estimate the average velocity and densities of the vehicle at each cell. The observation measurements are only available at some segments boundaries of the roadway. In previous works, The results show that the PF is more accurate than the UKF and EKF. Additionally, PF can be used with the microscopic models or can also be extended to consider platoons or groups of vehicles in an attempt to improve the accuracy of the prediction and reduces the computational time such as in [125].

However, due to observation measurements are only received at some boundaries between segments and averaged with possibly irregular time intervals, the PF accuracy might be decreased. In this thesis, past measurements and dynamics of the system are used to attain the conditional distribution of the traffic state model. It has been shown that when the observation is unavailable at all of the

2. BACKGROUND AND LITERATURE REVIEW

road segments boundaries that the PF accuracy can decrease at the boundaries without measurements.

Chapter 3

Traffic Congestion Avoidance Approach

3.1 Introduction

Vehicular traffic congestion is a significant problem that arises in many cities. This is due to the increasing number of vehicles that are driving on city roads of limited capacity. The vehicular congestion significantly impacts travel distance, travel time, fuel consumption and air pollution. Avoidance of traffic congestion and providing drivers with optimal paths are not trivial tasks. The key contribution of this chapter consists of the developed approach for dynamic calculation of optimal traffic routes. Two attributes (the average travel speed of the traffic and the roads' length) are utilized by the proposed method to find the optimal paths. The average travel speed values can be obtained from the sensors deployed in smart cities and communicated to vehicles via the Internet of Vehicles and roadside communication units. The performance of the proposed algorithm is compared to three other algorithms: the simulated annealing weighted sum, the simulated annealing technique for order preference by similarity to the ideal solution and the Dijkstra algorithm. The weighted sum and technique for order preference by similarity to the ideal solution methods are used to formulate different attributes in the simulated annealing cost function. According to the Sheffield scenario, simulation results show that the improved simulated annealing technique for order preference by similarity to the ideal solution method improves the traffic performance in the presence of congestion by an overall average of 19.22% in terms of travel time, fuel consumption and CO_2 emissions as compared to other algorithms; also, similar performance patterns were achieved for the Birmingham test scenario.

3.1.1 Main Contributions

This chapter presents and evaluates a new multi-objective improved simulated annealing technique for order preference by similarity to the ideal solution (ISATOPSIS) algorithm for congestion avoidance based on an IoV communication system. The main objective in ISATOPSIS is to provide various route decisions according to different objectives in order to meet the diverse navigation requirements of drivers; for example, the minimum TT, TD, fuel consumption or a trade-off of all conditions. In this chapter, two other algorithms have been implemented: simulated annealing weighted sum (SAWS) and the simulated annealing technique for order preference by similarity to the ideal solution (SATOPSIS) for compression purposes. The cost function of SAWS has been formulated using the weighted sum method. The cost function of SATOPSIS and ISATOPSIS has been formulated using the multi-attribute decision making (MADM) method, which is called the technique for order preference by similarity to the ideal solution (TOPSIS) method [15]. The results of the proposed algorithm ISATOPSIS have been compared to the shortest path Dijkstra algorithm (DA), SAWS and SATOPSIS.

1. ISATOPSIS allows transition from a good solution to a worse solution under a strict condition. This allows the algorithm to find the global optimal solution and avoid becoming stuck in local optimal solutions.
2. ISATOPSIS can work for a dynamic path planning by collecting real-time traffic data from IoV and efficiently finding alternative routes for the driver.
3. ISATOPSIS can optimize more than one criteria using the MADM TOPSIS method, which allows alternative routes to be judged on different criteria.
4. ISATOPSIS periodically detects and avoids congestion by selecting the paths that have the minimum traffic, CO_2 emissions, fuel consumption, as well as travel time. This is due to combining different navigation attributes in the cost function.

The remainder of the chapter is organized as follows: in Section 3.2, The details of SAWS, SATOPSIS and ISATOPSIS are given. In Section 3.3, a performance evaluation of ISATOPSIS is provided. Finally, the chapter conclusions of are drawn in Section 3.4.

3.2 System Description

IoV consists of two components: V2V and V2I communication. The V2V system is an on-board WSN which is installed in the vehicles themselves. The sensors allow the vehicles to send and receive information such as speed, location and direction [14]. The V2I system is a roadside unit network comprising some of the infrastructure related to smart cities, e.g. traffic sensors deployed along the roads and at intersections.

In this thesis, both systems have been used with the “hello” protocol [126] or beacon messages, which focus on tackling the problem of monitoring, traffic and reducing congestion. Figure 3.1 shows the V2V and V2I architectures. In this protocol, each vehicle will have an overview of the average speed and density of vehicles on the road network. This allows them to choose the optimal path to reach their destination. In this section, we describe our proposed system, by specifying data dissemination methodology, the road network model, Simulated annealing of SAWS and SATOPSIS and An improved simulated annealing TOPSIS algorithm.

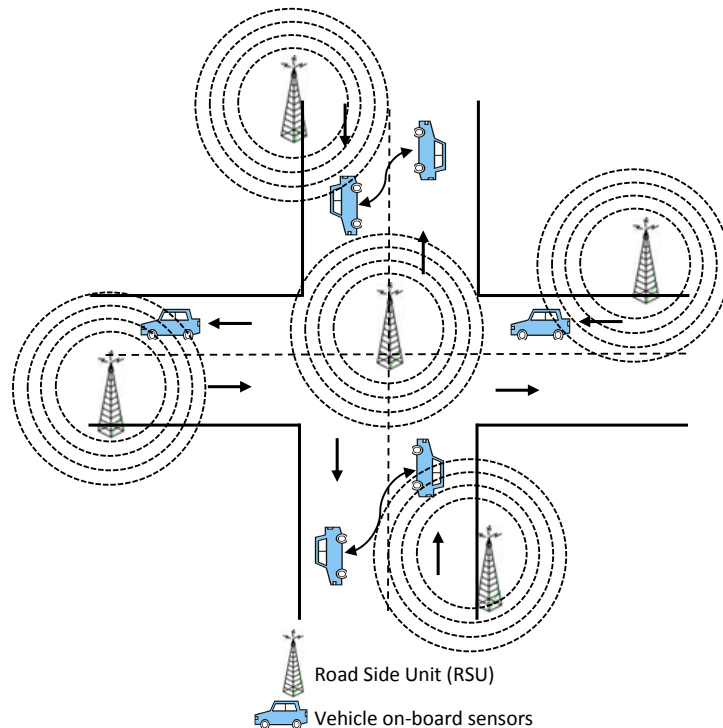


Figure 3.1: IoV road network infrastructure

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

3.2.1 Data Dissemination

The data has been transmitted using beacon messages and the proposed protocol works as follows: the vehicles transmit their average velocity and “roadId” to its neighboring RSUs through beacon messages. Each RSU holds a data structure contains the average speeds, roadIds and roads length of all vehicles within its transmission range. The average speeds are found from the speed measurements over the previous 5 seconds (one measurement a second). If the average speed is less than or equal to a velocity threshold which predetermined by the designer, the congestion detection is initiated, in which congested roads are identified. The RSU will then verify whether or not to broadcast the data from receiving beacon messages. The data will be used if the RSU does not receive a duplicate message with the same roadId. Whenever the RSU receives a new beacon, it updates its data structure and broadcasts the data to vehicles within its transmission range. As a result, congested roads can be excluded from the map and a new route calculated at the application layer of V2V communication using the ISATOPSIS algorithm.

3.2.2 Road Network Formulation

The road network can be modeled as a directed graph $G = (N, E)$, where N corresponds to the intersections (Nodes), and $E = \{e_1, e_2, \dots, e_i\}$ corresponds to the road segments (edges). The road matrix A can be formulated as follows: Suppose each intersection contains n roads; each of roads contains j attribute value in the road map:

$$A = \begin{matrix} & C_L & C_S \\ A_1 & \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \\ \vdots & \vdots \\ x_{n1} & x_{n2} \\ w_1 & w_2 \end{bmatrix} \\ A_2 & \\ \vdots & \\ A_n & \end{matrix} . \quad (3.1)$$

The normalized road matrix R' has been obtained using the following equation

$$r_{kj} = \frac{x_{kj}}{\sqrt{\sum_{k=1}^n (x_{kj})^2}} \quad \text{where } k = 1, \dots, n; \quad j = 1, 2 \quad , \quad (3.2)$$

$$R' = \begin{matrix} & C_L & C_S \\ A_1 & \begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \\ \vdots & \vdots \\ r_{n1} & r_{n2} \\ w_1 & w_2 \end{bmatrix} \\ A_2 & \\ \vdots & \\ A_n & \end{matrix} . \quad (3.3)$$

where $r = \{r_{kj} | k = 1, \dots, n; \quad j = 1, 2\}$ are the normalized performance values of each C_L and C_S , respectively. $X = \{x_{kj} | k = 1, \dots, n; \quad j = 1, 2\}$ denotes the set of performance values of each C_L and C_S , respectively. $w = \{w_j | j = 1, 2\}$ denotes the set of weights, $V = \{v_1, v_2, \dots, v_j\}$ is the set of vehicles and $A = \{A_k | k = 1, \dots, n\}$ are the alternative roads for each vehicle in V . Every vehicle v_j periodically sends a message msg_j that contains $\{roadId_j, averagespeed_j, position_j, route_j, destination_j\}$ to the neighbouring RSUs.

Two parameters have been used in our optimization:

1. Road Length $C_L = \{r_{kj} | k = 1, \dots, n; \quad j = 1\}$ represents the normalized length in a directed graph G for each alternative in R' .
2. Average Velocity $C_S = \{r_{kj} | k = 1, \dots, n; \quad j = 2\}$ represents the normalized average speed of each vehicle at a certain period in R' .

3.2.3 The Simulated Annealing for Routing Avoidance

SA is an optimization approach first proposed by [41] that imitates the process of annealing in mineralogy. It allows transference from a given solution to a worse solution under strict conditions. This allows the algorithm a mutation to move from local minima or maxima towards the global optima.

SA begins with a set of randomly chosen solutions. Each iteration produces a new solution of the state vector, which is found based on the cost function. A new solution with a high cost is accepted immediately. However, a solution with

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

a lower cost than the previous can be accepted with a transition probability. In this thesis, K random paths have been generated from matrix A . Figure 3.2 shows how the paths are generated. An initial path is set up from the source to the destination. Then, a new neighbouring to the source road from the road matrix A is selected randomly using a uniform distribution where each road has the same probability to be chosen. If the path is completed or the destination is reached, the feasibility of the path has been checked in order to make sure that this path is valid.

SA has been used with two different cost functions (weighted sum and TOPSIS methods) to select the optimal path from the K random paths. Every v_j in V has a set of alternative paths from M_k . Where, M_k is a matrix of K random paths generated from R' . Every path in M_k contains the number of roads A_k and the cost function of each path has been computed as the sum of the costs of all the roads it contains.

Algorithm 1 describes the procedure of choosing a path from K random paths, where X_c is the current solution, which is generated randomly from M_k . T is the temperature parameter, which is moderately decremented with time. The constant α is the cooling rate used to gradually decrease the value of T . When the temperature parameter has a very high value i.e. $T \rightarrow \infty$, a new path X_n is selected randomly from M_k . The cost function is evaluated for X_n ($N(X_n)$) and compared to the previous value of the cost function ($C(X_c)$). If the cost function is higher than the previous value, then the solution is accepted. Even if the new solution is not appropriate (meaning the cost of the new solution is less than or equal to the current solution), it is accepted with some acceptance probability. This helps to expand the search and avoids local optima. When T approaches zero paths with high cost have a high probability of being accepted.

The SAWS and SATOPSIS find up to 3 alternatives for vehicles that have the same source/destination. When the optimal paths are found, they are ordered based on the cost function. The vehicles that have the same source/destination, are distributed on these three optimal paths. This will ensure the vehicles are shared between the paths and ensures the traffic load is balanced on the map.

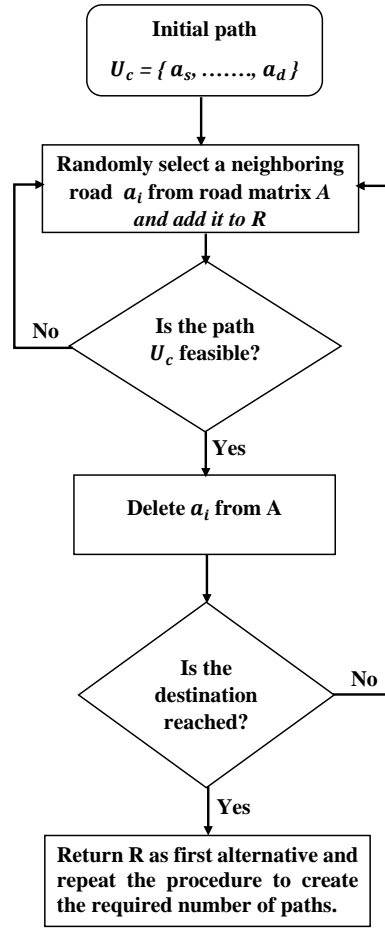


Figure 3.2: The procedure of generating a random path

3.2.4 An Improved Simulated Annealing for Routing Avoidance

In this section, SA has been implemented for dynamic path planning using the TOPSIS cost function method. The decision-making process of the proposed approach is constructed as follow:

Off-line computation of path planning

SA begins with off-line route calculation, in which every v_j in V has a set of roads from R' and every road A_k in R' has a cost function formulated using TOPSIS method. The algorithm description of the SA is outlined in Algorithm 1, except the Step 1 where X_c is the current search solution or an initial feasible path,

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

Algorithm 1 The Simulated Annealing algorithm for enhancing mobility

- 1: $X_c = X_{c_0}$ Initial random solution
 - 2: $T = T_0$ An initial temperature
 - 3: $\alpha =$ Cooling rate
 - 4: $s_b =$ Current best solution
 - 5: $s_b \leftarrow X_c$
 - 6: **While** $T > T_m$ Where T_m is the minimum temperature
 - 7: Generate a random neighbour solution X_n from R_k
 - 8: **If** $N(X_n) > C(X_c)$
 - 9: Move to X_n
 - 10: Accept change $s_b \leftarrow X_n$
 - 11: **Else If** $N(X_n) \leq C(X_c)$ **Then**
 - 12: Move to X_n with transition probability
 - 13: $P_t = 1/1 + \exp(C(X_c), N(X_n), T)$
 - 14: **Endif**
 - 15: $T = \alpha T$
 - 16: **Endwhile** (if $T < T_m$)
 - 17: **Return** s_b
-

which is an optimal path from R_k . When the temperature parameter has a very high value the new search solution X_n in Step 7 is constructed based on X_c as follows:

1. An initial optimal path $X_c = \{r_s, r_1, \dots, r_i, r_{i+1}, \dots, r_{l-1}, r_l, r_d\}$ where r_i means the i^{th} road segment.
2. The perturbation (see Figure 3.3) consist of the following three steps.
 - (a) Two roads r_i and r_l , called a base roads, are chosen randomly by using a uniform distribution in X_c path.
 - (b) A path is constructed, using r_i as an origin and r_l as a destination.
 - (c) The path $X_c = \{r_s, r_1, \dots, r_i, r_{i+1}, \dots, r_{l-1}, r_l, r_d\}$ replaced by $(r_i, r_{i'+1}, \dots, r_{l'-1})$ to given a new path $X_n = \{r_s, r_1, \dots, r_i, r_{i'+1}, \dots, r_{l'-1}, r_l, r_d\}$.
3. Check the feasibility of the new path.
4. If its not feasible then repeat the process. Otherwise, use SA as in Algorithm 1 and compare the cost of the new path with the previous path.

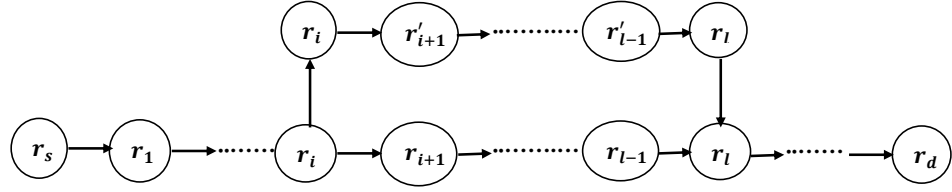


Figure 3.3: The procedure for constructing a new path X_n based on an initial path X_c

On-line computation of path planning

As discussed in the off-line computation section, the vehicles use the route generated by off-line path planning to travel through the city, the on-line path planning is then triggered to automatically compute an alternative route when congestion is detected as follows: When the vehicle reaches an intersection and enters the RSU transmission range, it will receive updated data with the table of congested roads. Then, the vehicle evaluates its current route. If the evaluation shows that the current route has not been affected by the updated data, the vehicle will keep traveling along the current route. Otherwise, if the vehicle is likely to enter a congested road, SA will be activated and reloaded with the updated search space. The updated search space contains the current status of the vehicle, its current location and the new cost of the road segments. The alternative route will be computed from the updated search space to allow the vehicle to travel from its current location to the destination. Figure 3.4 shows the procedure of the congestion avoidance using ISATOPSIS.

3.2.5 Approaches for Weights Calculation

In this chapter, the Standard Deviation (SDV) method is used to determine the weights of multiple objectives. The weight in MADM problem reflects the relative importance of the various objectives. The weights of different criteria have been normalized to transform the scales and units into common measurable units using (3.2).

Here, $M' = (R')_{m \times n}$ is the matrix after range normalization.

$$R'_{kj} \in [0, 1] \quad k = 1, \dots, n; \quad j = 1, 2$$

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

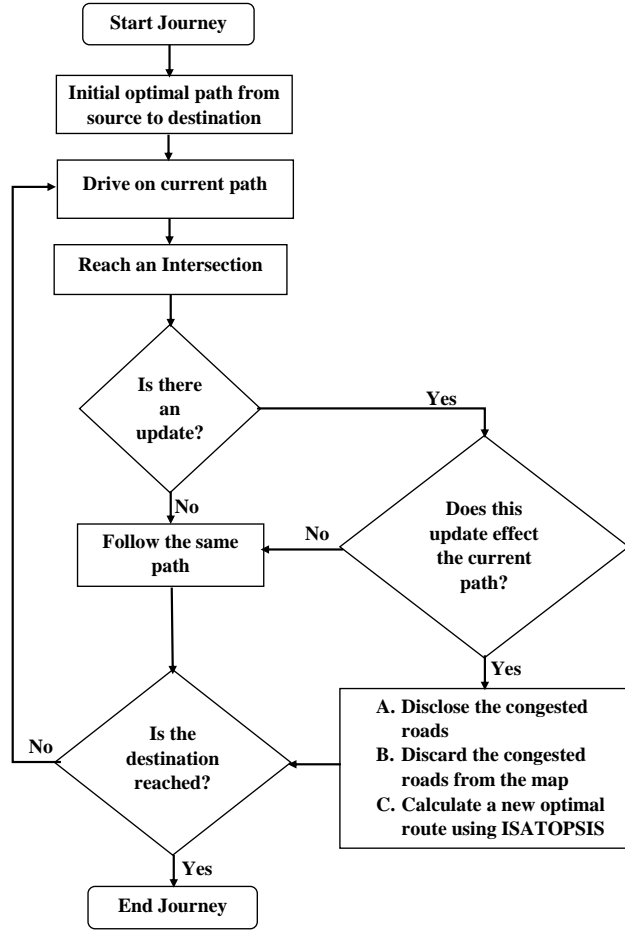


Figure 3.4: Flow chart of the SA congestion avoidance mechanism

SDV_j is the standard deviation that is calculated independently for every j^{th} criterion using the normalized matrix $M' = (R')_{m \times n}$ as shown in (4):

$$SDV_j = \sqrt{\frac{1}{n} \sum_{k=1}^n (R'_{kj} - \bar{R}_j)^2} \quad , \quad (3.4)$$

where

$$\bar{R}_j = \frac{1}{n} \sum_{k=1}^n R'_{kj} \quad . \quad (3.5)$$

\bar{R}_j is the mean of the values of the j^{th} criterion in C_L and C_S after normalization and $j = 1, 2$. From (4) the weight (w_j) of the criterion(j) in road matrix A can

be defined as:

$$w_j = \frac{SDV_j}{\sum_{j=1}^2 SDV_j} \quad . \quad (3.6)$$

3.2.6 Simulated Annealing Weighted Sum Approach

A multi-objective problem is often solved by combining the multiple objectives into one single-objective scalar function. This approach is in general known as the weighted-sum or scalarization method. In this chapter, the cost function of the simulated annealing has been formulated using the weighted sum method as below:

$$f = \text{Max}\{w_1 C_L + w_2 C_S\} \quad , \quad (3.7a)$$

$$C_L = \sum_{k=1}^n r_{k1} \quad , \quad (3.7b)$$

$$C_S = \sum_{k=1}^n r_{k2} \quad . \quad (3.7c)$$

3.2.7 TOPSIS Cost Function Formulation

The SATOPSIS and ISATOPSIS cost functions have been implemented using the TOPSIS method that can determine the best alternative route based on the concepts of a compromise solution. The compromise solution can be regarded as choosing the solution with the shortest Euclidean distance from the ideal solution and the farthest Euclidean distance from the negative ideal solution. The procedures of TOPSIS can be described as follows:

1. Calculate the weighted normalized ratings by using the normalized matrix from (1) and (2)

$$z_{kj} = w_j r_{kj} \quad . \quad (3.8)$$

2. Calculate the Positive and Negative Ideal Solutions (PIS) and (NIS) which are the maximum and the minimum values of the criterion (j) in C_L and C_S , respectively. We can formulate the normalized road matrix and obtain

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

the positive and negative ideal solutions as follows:

$$PIS = H^+ = \{z_1^+, \dots, z_j^+\} \quad , \quad (3.9a)$$

$$NIS = H^- = \{z_1^-, \dots, z_j^-\} \quad . \quad (3.9b)$$

3. Calculate the separation (D_k^* and D_k^-) from PIS (H^+) and NIS (H^-) for the alternative paths as follow:

$$D_k^* = \sqrt{\sum_{j=1}^2 (z_{kj} - z_j^+)^2} \quad k = 1, \dots, n \quad , \quad (3.10a)$$

$$D_k^- = \sqrt{\sum_{j=1}^2 (z_{kj} - z_j^-)^2} \quad k = 1, \dots, n \quad . \quad (3.10b)$$

4. Calculate the cost function of SA by finding the similarities to PIS using.

$$Y_k^* = \frac{D_k^*}{D_k^* + D_k^-} \quad Y_k^* \in [0, 1] \quad \forall k = 1, \dots, n \quad . \quad (3.11)$$

However, in this thesis, the ranking procedure of the TOPSIS method has been avoided by using the SA optimization algorithm. The cost function of ISATOPSIS approach has been implemented by estimating the similarities to PIS as in ((??)) for each road on the road matrix R' . The vehicle matches roads Id on the current path that is driving on it with the roads Id from the road matrix R' in order to obtain the values of (Y_k^*). Then, the total route cost of a vehicle is estimating by adding all the values of (Y_k^*) for roads on it.

3.3 Performance Evaluation

This section describes the performance evaluation and the results of the proposed solution. To manage and monitor the vehicle's mobility, we have used the Simulation for Urban Mobility (SUMO) version 0.22.0 [127] with the Traffic Control Interface (TraCI) which is an interface between road traffic and network simulators [128]. Two scenarios have been used to test and validate the proposed algorithm (Scenario of Sheffield city and Birmingham city).

3.3.1 Scenario of Sheffield City

The proposed system is simulated using open source software: Open Streets Map (OSM) [129] to import a real-time map of Sheffield city centre as shown in Figure 3.5a, b with and with out parks, lakes and buildings. The congested roads are zoomed in on in Figures 3.6c, d and e, respectively.

For the first test scenario we have chosen the city centre of Sheffield since this is a typical urban environment, which contains a variety of roads with different characteristics. For example, there are single lane roads, the dual carriageway ring road and junctions with restricted access/egress. The level of congestion on these roads varies both geographically and with time. This relationship between congestion and location/time is also present in all major cities. As a result, we think it is reasonable to suggest that the results from Sheffield in terms of the relative performance of each method can be generalized to other cities as well. The only difference will be that the absolute value such as mean trip time may change depending on the size of the city considered.

Table 3.1 shows the parameters that have been used in the simulation, whereas the vehicles speed and velocity threshold parameters have chosen by the designer using UK road laws as a guide. The other parameters have chosen based on the open street map and SUMO specification.

Table 3.2 shows the parameter of SA has been used in this simulation of both the off-line and on-line computation, whereas the values of T and α used

Table 3.1: Simulation parameters as configured in the SUMO implementation of Sheffield scenario

Simulation parameters	Value
Map dimension	4 km×3.5 km
Simulation time	2500 sec
Vehicle speed	0-15 m/s
Velocity threshold	7 m/s
MAC/PHY	IEEE 802.11p
Vehicle density	300-2100 Vehicle
Route generator	SUMO

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

for the proposed SA based approach. When making these selections the following considerations had to be made:

1. A large initial temperature T allows for an exhaustive search, but leads to a large computation time. Reducing this initial value will reduce the computation time required at the expense of making it less likely that the globally optimal solution will be achieved.
2. As the value of α controls the rate at which T decreases, a larger value gives a quicker decrease. This results in a shorter computation. However, this will also result in the algorithm running for fewer iterations, making it less likely to reach the truly optimal solution.

We suggest the values of T and α given in Table 1 to give a suitable trade-off between the two performance measures considered. Note, there are different values for the off-line and on-line cases as a shorter computational time is more desirable for the on-line case than the off-line case as real time implementation would be required.

The Emissions from Traffic (EMIT) model [130] has been employed, which is a simple statical model to the fuel consumption and vehicle emissions based on vehicle speeds and accelerations in the SUMO simulator. In this thesis, the fuel consumption and CO_2 emissions have been computed based on parameters that have been considered in the cost function (vehicle speed and road length).

The proposed algorithms have been implemented for the different vehicular environments to optimize the traffic scenario. The SAWS optimized the average travel time taken by vehicles to reach their destination, whereas ISATOPSIS has improved most criteria (the travel time, fuel consumption and CO_2 emissions)

Table 3.2: The tuned SA algorithm parameters of off-line and on-line search

Parameters	Values
T off-line	500 °C
α off-line	0.998
T on-line	25 °C
α on-line	0.992



(a) The city centre of Sheffield



(b) SUMO map of Sheffield city centre

Figure 3.5: The city centre of Sheffield and SUMO map

3. TRAFFIC CONGESTION AVOIDANCE APPROACH



(a) Traffic congestion area 1



(b) Traffic congestion area 2



(c) Traffic congestion area 3

Figure 3.6: The zoomed places showing traffic congestion on some roads

which are used in this thesis. The obtained result of the proposed method has been compared with SAWS, SATOPSIS and DA algorithms.

We initially imported the Sheffield city centre from an open street map tool and converted it in SUMO simulator using “Netcovert” command. Ten independent Monte Carlo simulations were conducted and the mean results reported.

The objective of the ISATOPSIS algorithm is to optimize the traffic flow (minimize the travel time, fuel consumption and CO_2 emission). The ISATOPSIS combines the SA algorithm and TOPSIS method as a cost function to optimize different conflicting criteria such as the length and the average speed which are considered the most important parameters in selecting the best route. It has successfully minimized the average travel time, fuel consumption and CO_2 emission. However, this has led to a slightly increased average travel distance that has not affected the overall traffic efficiency.

SATOPSIS applied then the SA algorithm and TOPSIS method to estimate the best route of vehicles based on the static traffic information that are the length and the free flow speed of the road segments. However, the SATOPSIS performance is similar to the Dijkstra algorithm to a particular stage. It might only provide incomplete optimal outcomes. In contrast, ISATOPSIS is proposed to cope with the problem of path planning based on the intelligent real-time traffic information. The optimal route is estimated automatically based on real-time traffic information and traffic congestion situations utilising ISATOPSIS approach. The selected route can be the smallest travel time, shortest in distance or better in the traffic flow. ISATOPSIS provides not the only alternative best route to the driver by estimating various criteria of the road but also adapting the route dynamically by periodically detecting the congestion based on real-time traffic information communicating among the vehicles or RSUs tools. Moreover, the ISATOPSIS provides the best average speed with the smallest amount of fuel consumption that effects on green intelligent transportation.

In this thesis, two criteria have been used in order to optimize the routes of the drivers that are the length of the roads and their average speeds. These parameters have been chosen due to their significant impact on the travel time according to the speed, distance and time relationship as in the equation below.

$$Time = \frac{Distance}{Speed}. \quad (3.12)$$

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

The higher the travel speed, the shorter the length of the road segment, the lower the travel time elapsed by the driver to travel from the source to the destination. The travel time and the speed have a direct effect on fuel consumption and CO₂ emissions results. If the travel speed is very low the traffic density will be very high and the waiting time will be increased which in turn increases the fuel consumed by the engine. Results of CO₂ emissions are directly related to the results of fuel consumption. The longer travel distance, the larger waiting time, the more fuel consumed by the engine, resulting in higher CO₂ emissions.

Four different matrices have been measured in the performance evaluation:

- **Mean Travel Time (MTT)**: average travel time of all vehicles.
- **Mean Travel Distance (MTD)**: average travel distance taken by vehicles.
- **Fuel consumption (FC)**: average fuel consumption taken by vehicles
- **CO₂ emission**: average CO₂ emission of all vehicles

Table 3.3 shows the average values of all calculated metrics for all algorithms. This result demonstrates that SAWS minimizes the travel time comparing with DA and SATOPSIS. However, it increases the travel distance because it routes the vehicles along the longest free flow paths. The DA has the minimum travel distance comparing with other algorithms because it routes the vehicles to the shortest path. However, it has the worst performance in terms of travel time, fuel consumption and CO₂ emissions because most vehicles traveling with DA are stuck in congestion. On the other hand, SATOPSIS attempts to minimize

Table 3.3: The average results obtained by DA, SAWS, SATOPSIS and ISATOPSIS in the tested scenarios

Method	MTT (sec)	MTD (m)	FC (ml)	CO ₂ (g)
DA	544.45	3396.84	496.603	873.206
SAWS	432.55	3868.76	473.194	809.957
SATOPSIS	439.29	3551.15	445.629	635.079
ISATOPSIS	365.153	3656.367	428.904	560.668

3.3 Performance Evaluation

all the matrices by considering multiple attributes in the cost function. It has better performance compared with SAWS for except the travel time, which is converged to some extent with SAWS. In comparison, ISATOPSIS decreases the MTT, FC and CO_2 emissions when compared to DA, SAWS and SATOPSIS. This reduction is due to the re-routing of all vehicles once the congestion is detected. In addition, these results demonstrate the benefits of considering the multiple attribute cost function performed by the ISATOPSIS algorithm to avoid the congestion. However, this re-routing slightly increased the MTD comparing with DA and SATOPSIS, respectively. This increase is due to the dynamic re-routing of vehicles and, thus an extra path has been added to the original route.

Table 3.4 shows the average (over different vehicle numbers) variances (Var) for the performances measures that have been considered. As the variance values for the proposed method is lower than the comparison methods this shows that the proposed approach is more consistent than the comparison methods.

Figure 3.7 graphically shows the average travel time of all of the algorithms. It is clear from the figure the average travel time has a direct relationship with vehicle density. As is foreseeable, the average travel time increases as the number of vehicles increases. This is because of the greater number of vehicles in the traffic jam, which increases the average travel time as is shown for DA in Figure 3.7. The SAWS and SATOPSIS travel time remain more constant and lower than the DA. This is due to the distribution of vehicles having the same source/destination over more than one route. In comparison, the ISATOPSIS has significantly improved the average travel time since it re-routes the vehicles to avoid congested roads. In addition, ISATOPSIS pays attention to the congestion which is not considered in the other algorithms and attempts to select an optimal path by finding a trade-off

Table 3.4: The overall average variance results obtained by all algorithms in the tested scenarios

Method	Var MTT (sec)	Var MTD (m)	Var FC (ml)	Var CO2 (g)
DA	88.202	248.59	96.83	85.47
SAWS	65.65	185.819	73.61	61.77
SATOPSIS	44.157	136.46	67.408	39.0625
ISATOPSIS	26.86	88.25	60.79	32.49

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

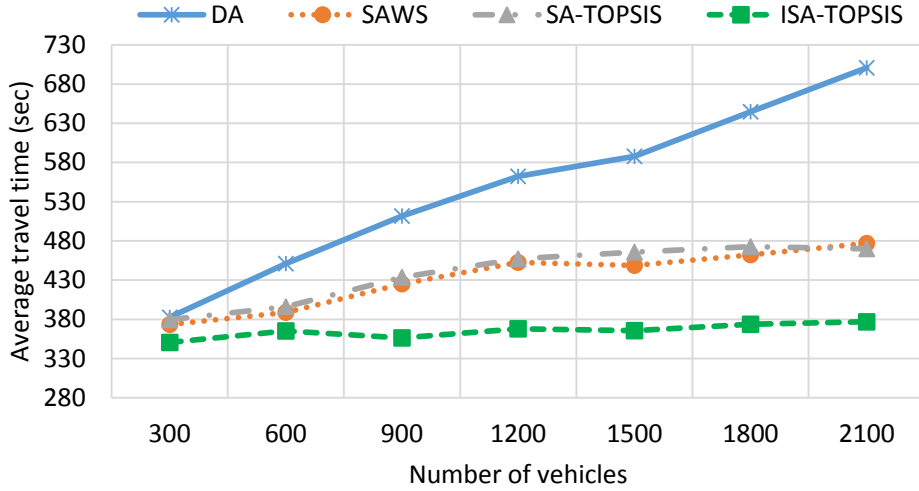


Figure 3.7: Average travel time

between the conflicting objectives. Figure 3.8 illustrates the average path length result for all of the methods considered. The SAWS increases the travel distance compared with DA, SATOPSIS and ISATOPSIS. This is due to the fact that SAWS chooses the paths with the highest average travel speed and distributes the vehicles on them to avoid generating congestion. On the other hand, this result shows that ISATOPSIS can find a compromise by minimizing effectively MTT, FC and CO_2 due to its ability consider multiple traffic information. However, this reduction leads to a slight increase in the travel distance compared with DA and SATOPSIS, since ISATOPSIS utilizes the traffic information and re-routes the vehicles to avoid the congested roads, where DA and SATOPSIS have a constant travel distance that is not affected when the congestion occurs.

Figure 3.9 shows the fuel consumption results obtained by the four algorithms. We can see the impact of taking the longest free flow path and the shortest congested route on the traffic efficiency and the fuel consumption. The fuel consumption result is directly related to the travel time, travel speed, waiting time and travel distance. The highest average speed, the longest travel distance and the most waiting time leads to higher fuel consumption. The figure shows that DA consumes as much fuel as SAWS for low vehicle densities. This is due to the effect of choosing the longest traveled path and waiting times taken by SAWS and DA, respectively. However, with increasing numbers of the vehicles on the city roads the figure shows that SAWS fuel consumption is much better than the DA algorithm. This is due to the fact that the longest waiting time is taken by

3.3 Performance Evaluation

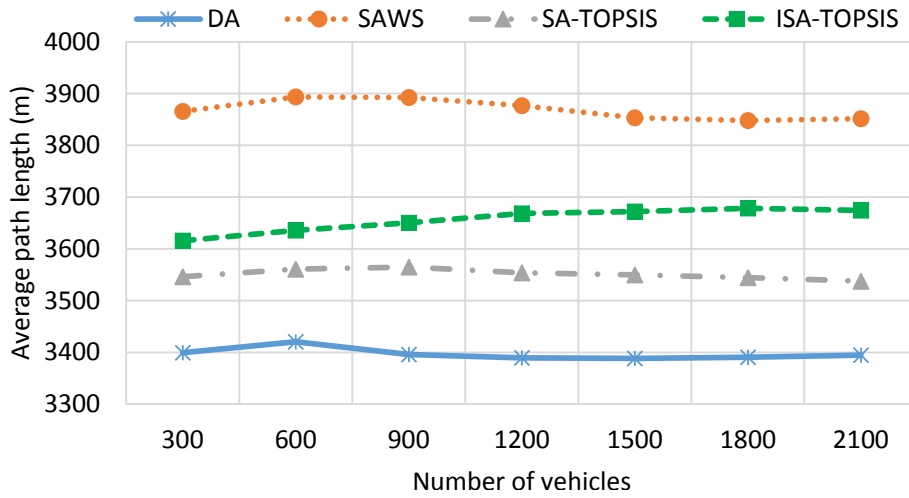


Figure 3.8: Average travel distance

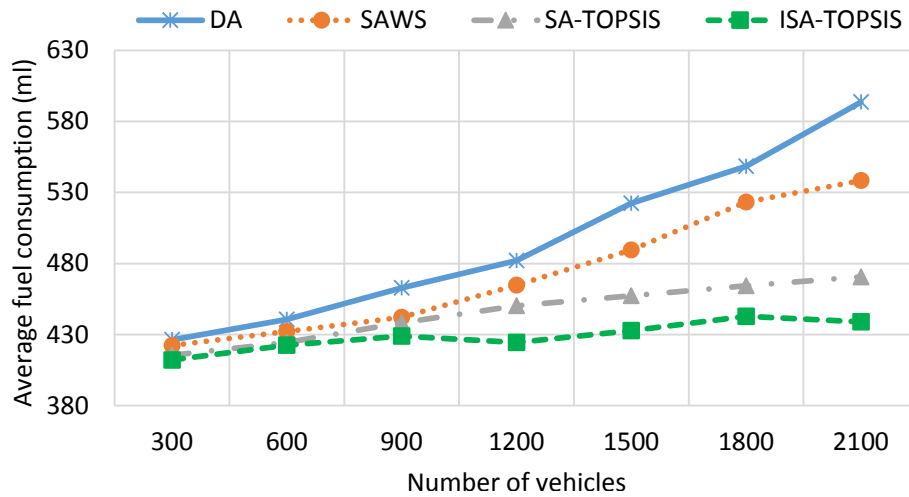


Figure 3.9: Average fuel consumption

vehicles using DA in the congested area. According to this figure, SATOPSIS and ISATOPSIS consume less fuel when compared with the others. The ISATOPSIS has better fuel consumption due to less waiting time, the best average speed and an optimal path that is selected based on the different navigation criteria. In addition, ISATOPSIS pays attention to the congestion with avoidance mechanism that helps to re-route the vehicles and avoid the traffic jams.

Figure 3.10 depicts the CO_2 emissions recorded from all of the algorithms. Results of CO_2 emissions are directly related to the results of fuel consumption. The longer travel distance, the larger waiting time, the more fuel consumed by the

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

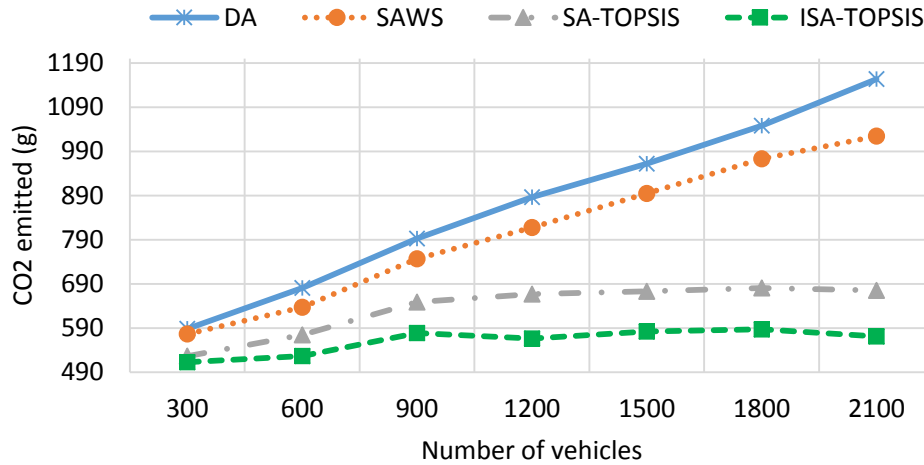


Figure 3.10: Average CO2 emission

engine, result in higher CO_2 emissions. High vehicle densities or traffic congestion leads to longer waiting times on the roads, so the fuel consumption as well as CO_2 emissions are increased. It is clear from the figure that ISATOPSIS has the lowest average CO_2 emissions compared with the other algorithms. This is due to it having the best average travel speed and the optimal path (multi-attribute cost function) being obtained by ISATOPSIS. The SATOPSIS comes in second place in terms of CO_2 emissions compared with SAWS and DA. Both SAWS and DA have the worst CO_2 emissions due to a large amount of fuel consumed by the vehicles using them.

Figure 3.11 illustrates the average travel speed obtained by all of the algorithms. The ISATOPSIS has recorded the best average travel speed compared with other methods at all vehicle densities. This is due to the congestion avoidance mechanism and providing the vehicles with alternative paths to avoid the congested roads. DA has the worst average travel speed. This due to a large number of vehicles being stuck in traffic congestion. We can see the impact of travel speed on the traffic efficiency (see Figures 3.7 and 3.8), despite the SAWS and SATOPSIS having better performance comparing with DA. However, they have a relatively poor efficiency compared with ISATOPSIS, due to not paying attention to the congestion avoidance mechanism when traffic jams occur.

Combining all the results, it is deduced that by using ISATOPSIS and considering multiple traffic information, the trip time, the fuel consumption as well

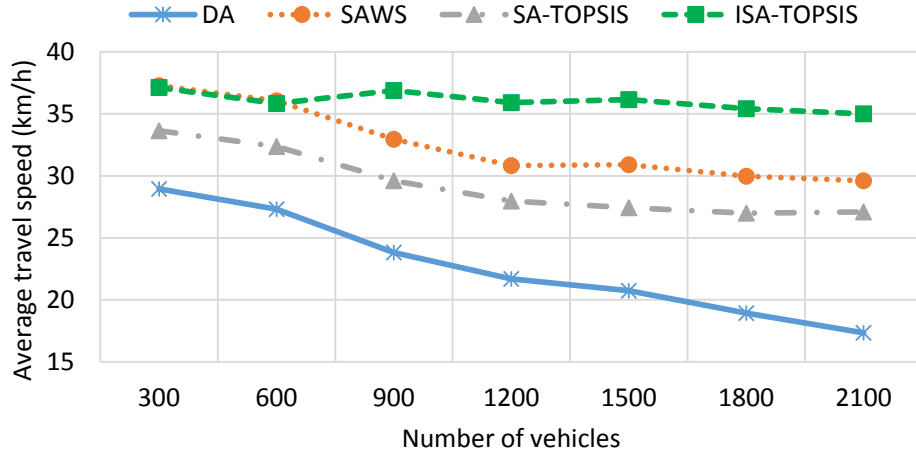


Figure 3.11: Average travel speed

as CO_2 emissions of vehicles are optimized, in order to reach the destination via the optimal path.

3.3.2 Scenario of Birmingham City

For the second test scenario a small section of Birmingham city centre has been imported using OSM. Figure 3.12a, b respectively, show the imported area in SUMO simulator with and without parks, lakes and buildings.

Table 3.5 shows the parameters that have been used in this scenario, where the number of vehicles has been decreased due to the smaller map size considered in this scenario. Vehicles speed and velocity threshold parameters have been chosen by the designer, again using UK road laws as a guide. The other parameters have been chosen based on the open street map and SUMO specification. The parameters for the SA algorithm are the same as have been used for the Sheffield test scenario and are summarized in Table 4.2. ISATOPSIS, SATOPSIS, SAWS and DA algorithms have also been tested for this scenario to allow further comparisons to be made.

Figures 3.13 and 3.14 show the mean travel time and fuel consumption results obtained using all of the algorithms being considered. They show that a similar performance pattern has been achieved as was for the previous scenario. Moreover, they show that the ISATOPSIS algorithm still has the best performance as compared with other algorithms. In conclusion, the relative performances of the

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

Birmingham New Street Train Station



(a) The section of Birmingham city centre under consideration



(b) SUMO section of Birmingham city centre under consideration

Figure 3.12: The section of Birmingham city centre and SUMO map

3.3 Performance Evaluation

Table 3.5: The simulation parameters configured in the SUMO of Birmingham city

Simulation parameters	Value
map dimension	2 km×1.5 km
Simulation time	1000 sec
Vehicle speed	0-15 m/s
Velocity threshold	7 m/s
MAC/PHY	IEEE 802.11p
Vehicle density	100-500
Route generator	SUMO

methods have not been changed by changing the city under consideration. However, the absolute values of the mean trip times and fuel consumption levels have changed due to the size difference in the maps used. The improved performance over the comparison methods is due to the fact that real-time traffic information has been used to continuously optimize trip time, fuel consumption and CO₂ emissions.

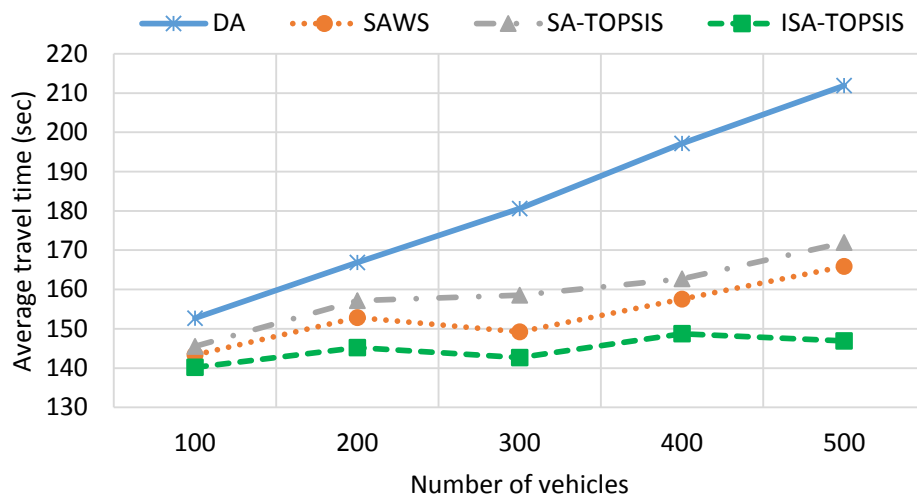


Figure 3.13: Average travel time Birmingham scenario

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

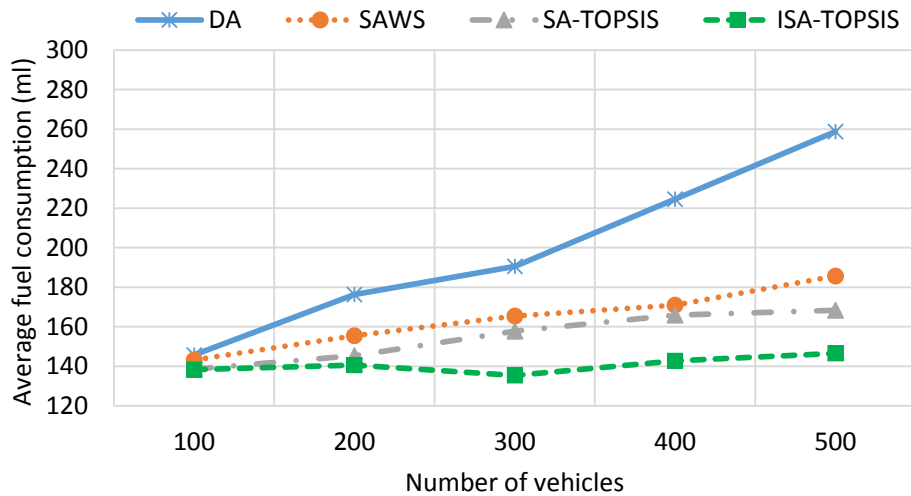


Figure 3.14: Average fuel consumption Birmingham scenario

3.4 Conclusions

In this chapter, the ISATOPSIS method has been proposed to address the traffic congestion problem in smart cities. The novelty of this thesis is in the use of the multi-objective cost function and dynamic route planning. Our proposed method can lead to a reduction in travel time, fuel consumption and CO_2 emissions. The proposed method has been implemented and tested using an open street map and the SUMO simulator. Results the Sheffield scenario show that the simulated annealing weighted sum method can reduce the travel time by an overall average of 19.93% compared with the DA and SATOPSIS. This is due to choosing the path with the highest average speed. However, it has a worse performance compared with the ISATOPSIS. Simulation results show that our proposed ISATOPSIS method can successfully find a trade-off between different navigation attributes, in order to provide each driver with the least congested path according to the road condition. As reported from the Sheffield test scenario, it is shown that ISATOPSIS can improve the traffic flow by an overall average of 19.22 % in terms of travel time, fuel consumption and CO_2 emissions when compared with Dijkstra, simulated annealing weighted sum and SATOPSIS algorithms. Moreover, similar performance patterns were achieved for the Birmingham based simulation. In future thesis we envisage the route selections being communicated back to intel-

ligent traffic light controls to help adaptively control their sequences to aid in achieving the overall optimal traffic flow for a smart city.

3. TRAFFIC CONGESTION AVOIDANCE APPROACH

Chapter 4

A Game Theory Approach for Congestion Control in Vehicular Ad Hoc Networks

4.1 Introduction

The increasing number of vehicles on road networks has put a great pressure on transportation systems. This leads to serious road traffic problems such as road accidents, increased travel times, fuel consumption and air pollution.

Recently, the appearance of the IoV [131], has been considered as an interesting challenge for the traffic research community and it provides a new direction for ITSs. The IoV foresees future vehicles as being connected, allowing the sharing of safety and non-safety related traffic data to enhance mobility and comfort. The main part of the IoV is VANETs that include different systems. Firstly, V2V communication systems that are on-board WSNs installed inside the vehicles [132]. Secondly, RSU or V2I communication system.

ITSs utilize VANETs to broadcast messages between connected vehicles. This helps TMSs to the control road traffic congestion, which reduces the number of road accidents, decreases travel times, fuel consumption and air pollution. ITSs have used VANETs for Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication systems. This allows the applications in ITS to communicate over short transmission ranges.

The DSRC community has adopted the use of the WAVE for supporting V2V and V2I communication systems [16]. WAVE emerged from the IEEE 802.11p and IEEE 609 protocols in the PHYSical layer (PHY) and the Medium Access Control (MAC) layer. This allows the applications in ITS to communicate over short transmission ranges. The European Telecommunication Standards Institute (ETSI) [18] has defined two kinds of safety application messages that can be transmitted through the Control CHannel (CCH) of WAVE protocol: Central

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

Access Messages (CAMs) or beacon messages and Decentralized Environment Notification Messages (DENMs) or event-driven messages.

CAMs are packets sent periodically between V2V or V2I communication systems and they contain traffic data about the status of individual vehicles e.g. speed, position and direction [133]. DENMs are event-driven messages which are generated in emergency cases and are sent periodically until the event or the hazard that caused the emergency has disappeared.

ITSs use these messages to provide the information required to vehicles to allow for efficient mobility and safe journeys for drivers. However, the continuous transfer of messages in vehicular ad hoc networks leads to a heavy network traffic load. This causes congestion in the wireless channel which degrades the reliability of the network and significantly affects the Quality of Service (QoS) parameters such as packet loss, throughput and average delay. Therefore, it is vital to adapt the transmitting data rates in a way that ensure that acceptable performance is achieved and that there is reliable communication of information between vehicles in smart cities. This means the information will be delivered in a timely manner to the drivers, which in turn allows implementation of efficient solutions for improved mobility and comfort in intelligent transportation systems.

In order to control the transmitted data rates in VANETs, this thesis proposes a non-cooperative game approach to formulate the wireless channel congestion problem. Non-cooperative game theory has been used in this thesis due to its ability to provide an analytical model for the communication and decision making problem in vehicular ad-hoc networks. Unlike cooperative game theory there is no requirement for the players in the game to communicate information relating to the optimisation of the data rate. This is advantageous as such communication would further contribute to the congestion problem.

In this thesis, each vehicle is represented as a selfish player and data transmission rates optimized. Then, the existence of a unique Nash equilibrium is derived. Two novel approaches have been proposed that are Game Theory Approach for Congestion Control (GTACC) and Non-Cooperative Game Approach for Congestion Control (NCGACC). The solution of the optimal game in GTACC is presented by using Karush-Kuhn-Tucker conditions and Lagrange multipliers. Simulation results show that the GTACC improves network efficiency in the presence of congestion by an overall average of 50.40%, 49.37%, 58.39% and 36.66%

in terms of throughput, average delay, number of lost packets and total channel busy time as compared to Carrier-Sense Multiple Access with Collision Avoidance mechanism.

The cost function of NCGACC has been formulated based on the sending rate, contention delay and priorities of vehicles in VANETs. The solution of the optimal game is presented by using the Newton-Raphson method. Simulation results show that the proposed NCGACC provides an adaptable solution that improves network efficiency and alleviates congestion on wireless channel by an overall average of 23.51%, 57.80%, 36.32% and 35.55% in terms of throughput, average delay, number of lost packets and collision probability, respectively, for the highway test scenario. Additionally, similar performance patterns are achieved for the urban test scenario.

The main contributions of the chapter are:

1. Two novel channel congestion mitigation approaches are proposed based on non-cooperative game theory to alleviate the data channel congestion in VANET networks. These methods can mitigate the channel congestion by adapting the vehicle sending data rate based on vehicles contention delay and priorities which are formulated in the utility function for every vehicle to achieve the desired fairness.
2. The existence of a unique pure strategy Nash equilibrium has been proved for the VANET congestion game.
3. The vehicle's utility function is formulated as a constrained non-linear optimization problem. Then, A utility function for each vehicle is solved using Karush Kuhn Tucker (KKT) conditions and Lagrange multipliers for the GTACC approach. The Newton—Raphson method has been used to solve the optimization problem and obtain the vehicle optimal data rate solution for NCGACC approach. This means each vehicle will use its optimal data rate that satisfies congestion mitigation and provides fair allocation of the network resources among vehicles.
4. An extensive performance evaluation is conducted for the proposed approach. This includes testing over both a highway and an urban based scenario. Comparisons are also made with the following algorithms: CSMA/CA,

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

the Network Utility Maximization (NUM) and Non-cooperative Beacon Rate and Awareness Control (NORAC) approaches. The results show that the proposed approaches are able to effectively optimize the data transmission rates to alleviate the channel congestion problem.

The remainder of the chapter is structured as follows: Section 4.2 provides the game approach formulation GTACC for congestion control and calculates the optimal solution for the game. In Section 4.4, a performance evaluation is provided. In Section 4.5, the simulation results is provided. Finally, conclusions are drawn in Section 4.6.

4.2 System Description

4.2.1 A Game Theory Approach Formulation:

V2V and V2I communication systems represent the main parts of VANETs. The V2V system consists of WSNs installed inside the vehicles. The sensors allow the vehicles to transmit and receive data such as speed, location and the direction of travel [134]. The V2I system is a RSU network, which consists of sensors deployed along the road and at the intersections. Vehicles can send information to, and receive information from, the RSUs.

In VANET systems every vehicle sends their data to the nearest vehicle or RSU which in turn broadcasts this data (CAMs or DENMs) to other neighbours within its transmission range. The congestion in the wireless channel occurs when many vehicles start to periodically send many messages (CAMs and DENMs) at the same time or relay a large volume of data across the network. To detect the congestion in the wireless channel different measurement approaches can be applied. These include calculating the number of packets queuing, estimating channel occupancy and sensing the channel usage levels [135, 136]. In this thesis, the congestion is detected in the channel by periodically comparing the channel usage with a threshold value as in [81].

Once road traffic congestion occurs, the vehicles begin to broadcast high data rate messages to their neighbours. In other words, each vehicle behaves selfishly and attempts to broadcast messages with a high data rate. This is without taking into consideration the transmitting rate of neighbouring vehicles, the buffer sizes

or the available channel capacity. In this case, a large number of messages are lost either on the wireless channel or in the MAC buffers.

The game theory has been widely applied to the problem of the wireless sensor channel congestion due to its ability to analysis and study of competitive decision-making including various players [42, 137, 138]. In this thesis a non-cooperative game theoretic approach is adopted in order to control the transmission rates in VANETs based on the vehicle's sending rate, contention delay, and vehicle's priority. Each vehicle is represented by a selfish player in the VANETs game. The Nash equilibrium (optimal solution) [139] is the data rates for which each individual can not improve their individual performance by altering their data rate while the rates of other vehicles remain constant.

Consider each RSU or vehicle that has a set of n vehicles (players) in its transmission range $V = \{v_1, v_2, \dots, v_i, \dots, v_n\}$ competing to send messages at the data rates (strategies) $s = [r_1, \dots, r_i, \dots, r_n]$ to their neighbours. Here, r_i is the sending rate of vehicle v_i . This is given by:

$$r_i = \begin{cases} r_b & \text{if not event driven,} \\ \{w_1 r_e + w_2 r_b\} & \text{if event driven,} \end{cases} \quad (4.1)$$

where r_b is the data rate of beacon packets or CAMs and r_e is the data rate of DENMs. Here, w_1 and w_2 are weight parameters that are selected by the designer to satisfy the system objectives and requirements.

Optimizing the transmission rates of vehicles and the RSUs is formulated as non-cooperative games $G1 = (V, (S_i)_{i \in V}, (\chi_i)_{i \in V})$ and $G2 = (V, (S_i)_{i \in V}, (\Theta_i)_{i \in V})$ where the game has the following key components:

- *Players*: A group of vehicles given by V have been considered where n represents the number of vehicles which are connected with the RSU or that are sharing the same transmission range.
- *Strategies*: The strategies represent the possible data transmission rate for each vehicle. Each player (vehicle) v_i can broadcast a maximum and minimum data rate of r_i^{max} and zero, respectively. Hence, $S_i = [0, r_i^{max}]$ is the set of available actions for player or vehicle i and the Cartesian product of strategy space for all players is $S = \prod_{i=1}^n S_i = [0, r_1^{max}] \times \dots \times [0, r_i^{max}] \times \dots \times [0, r_n^{max}]$.

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

- *Utility function*: The utility function of vehicle v_i is given by Θ_i and is used to improve its performance. This is achieved by optimizing the utility function with respect to r_i .

4.2.2 The Utility Function Formulation

In this chapter, two utility functions are formulated to represent the cost that each vehicle needs to pay as penalty for the broadcasting messages. The first utility function of the GTACC includes two factors that are the send data at a high rate (payoff function) and the priority of the vehicle (priority function). The utility function of the NCGACC includes three factors: send data at a high rate (payoff function), contention delay that gives the delay generated when many vehicles are transmitting at the same time and a priority attached to each vehicle determining which vehicles transmits data at a higher rate than the neighbour vehicles. Therefore, the vehicle utility functions comprises of below functions:

- *Payoff function*: The payoff function, $U_i(r_i)$, is modelled so that each vehicle obtains a greater payoff by improving its data rate. There are different kinds of cost functions that are generally utilized. These include linear, logarithmic, sigmoidal and exponential [140]. In this chapter, the logarithmic utility function has been used. This is because it is strictly concave on its domain. Hence, the payoff function of all vehicles v_i have been selected as follows:

$$U_i(r_i) = \log(r_i + 1). \quad (4.2)$$

Note, $+ 1$ has been added in (4.2) to avoid having the case $U_i(r_i) = -\infty$.

- *Maximum contention delay*: The maximum contention delay of vehicle (player) v_i has been denoted by $C_i(r_i; c_i)$. This function represents the number of vehicles affected by the data transmission contention along the road segment. According to [141], the maximum contention delay is calculated as follows:

$$C_i(r_i; c_i) = \frac{1}{Nr_{in}} - \frac{\tau}{B_o} \quad (4.3)$$

where $r_{in} = \sum_{i=1}^n r_i$ is the average packet arrival rate in packets per second, N is the total number of vehicles on the road network and n is the number of

vehicles that are sharing the transmission range. The fixed values τ and B_o are the packet size and maximum allowed bit rates, respectively.

In order to validate this equation let assume the $\tau= 800$ bytes and B_o bit rate 3 Mbps so the total transmission delay is 213 ms and the if the number of vehicle is $N= 100$ and the $r_i = 20$ packet per second then according the 4.3 the maximum contention delay will be equal to $- 1.63$ ms. According to [141] if the max contention delay less than zero this means the road segment suffer from contention on wireless channel.

- Priority function: The priority function, $P_i(r_i; p_i)$, is used to reflect the priority of each vehicle to send information. To distinguish between high and low priority vehicles, each vehicle v_i has to be punished based on its transmission rate (r_i) and a measure of its priority to send information. The priority objective function of vehicle v_i can be formulated as follows:

$$P_i(r_i, p_i) = \frac{r_i}{p_i} = \frac{r_i}{\frac{D_{i,j}}{R}}. \quad (4.4)$$

Here, $D_{i,j}$ is the distance between the original sender and the receiver, R is the transmission range of the RSU or vehicle v_i . Therefore, the furthest vehicles in the transmission range have a higher priority to send data while the vehicles close from the sender transmission range have a lower priority to send messages.

The distance parameter has been chosen due to that the vehicles near the event or accidents area have a good vision and they can see what happens on the road segment. Therefore, they are not required to send data at the maximum rate and consume the wireless channel. Unlike the vehicles that are far in distance from event area or out of the range of the original sender or RSU, they have no idea about the traffic state situation. Therefore, the vehicles that are the furthest from the original sender or considered last vehicles in the transmission range can send data at a high rate in order to increase the opportunities of receiving the traffic information related to the current traffic situations.

The utility function of vehicle v_i of GTACC is formulated as follows:

$$\chi_i(r_i, r_{-i}) = \alpha_i \log(r_i + 1) - \frac{\pi_i r_i}{p_i}. \quad (4.5)$$

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

The utility function of vehicle (player) v_i of NCGACC is formulated as follows:

$$\Theta_i(r_i, r_{-i}) = \alpha_i \log(r_i + 1) - \beta_i \left[\frac{1}{Nr_{in}} - \frac{\tau}{B_o} \right] - \pi_i \frac{r_i}{p_i}. \quad (4.6)$$

Here, α_i , β_i and π_i in both $\chi_i(r_i, r_{-i})$ and $\Theta_i(r_i, r_{-i})$ are player preference parameters of functions $U_i(r_i)$, $C_i(r_i; c_i)$ and $P_i(r_i; p_i)$, respectively, where α_i , β_i and $\pi_i > 0; \forall i \in V$. The values of α_i , β_i and π_i are selected by the designer to satisfy the system requirements and objectives. Note, r_{-i} is the data rate of all other vehicles except v_i .

4.2.3 Nash Equilibrium Proof and Existence

The Nash equilibrium gives the solution to the non-cooperative game. In the VANET congestion control games $G1 = (V, (S_i)_{i \in V}, (\chi_i)_{i \in V})$ and $G2 = (V, (S_i)_{i \in V}, (\Theta_i)_{i \in V})$, a strategy profile (data rate) $s^* \in S$ is a Nash equilibrium where $s^* = [r_1^*, \dots, r_i^*, \dots, r_n^*]$ if no vehicle (player) can improve its performance by altering its strategy, while the other vehicles (players) strategies remain fixed. The Nash equilibrium in this game is V-tuple $\{r_i^*\}_{i \in V}$ that satisfies:

$$\chi(r_i^*, r_{-i}^*) \geq \chi(r_i, r_{-i}^*) \quad \forall r_i^*, r_i \in S_i, r_i^* \neq r_i, \forall i \in V.$$

$$\Theta(r_i^*, r_{-i}^*) \geq \Theta(r_i, r_{-i}^*) \quad \forall r_i^*, r_i \in S_i, r_i^* \neq r_i, \forall i \in V.$$

Theorem 4.2.1 *Given a non-cooperative VANETs congestion games in strategic form $G1 = (V, (S_i)_{i \in V}, (\chi_i)_{i \in V})$ and $G2 = (V, (S_i)_{i \in V}, (\Theta_i)_{i \in V})$, $\forall i \in V$, where every strategy set S_i is compact and convex, $\chi_i(r_i, r_{-i})$ and $\Theta(r_i, r_{-i})$ are continuous function in a vector of strategies $s \in S$ and concave in S_i . Then, each game $G1$ and $G2$ has at least one pure-strategy Nash equilibrium.*

The strategy set $S_i = [0, r_i^{max}]$ for all vehicles (player), is closed and bounded. Hence, the set S_i is compact for all $i \in V$.

The set S_i is convex if and only if for any $a, b \in S_i$ and any $\theta = [0, 1]$,

$$0 \leq \theta a + (1 - \theta)b \leq r_i^{max}$$

Here, the point $\theta a + (1 - \theta)b \in S_i$. Therefore, the set S_i is convex; $\forall i \in V$.

Theorem 4.2.2 *A twice continuously differentiable payoff function χ_i and Θ_i are concave if and only if $\frac{\partial^2 \chi_i}{\partial r_i \partial r_j} \leq 0$, $\frac{\partial^2 \Theta_i}{\partial r_i \partial r_j} \leq 0 \forall i, j \in V$, and the Hessian matrix is Negative Definite (ND) for all $s \in S$.*

Proposition: To prove that both χ_i and Θ_i are concave, let's define the Hessian matrix of $\chi_i(s)$ and Θ_i , and $s = \{r_i, r_{-i}\}_{i \in V}$, as follows:

$$H_{\chi_i}(s) = \begin{bmatrix} f''_{11} & f''_{12} & \cdots & f''_{1n} \\ f''_{21} & f''_{22} & \cdots & f''_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f''_{n1} & f''_{n2} & \cdots & f''_{nn} \end{bmatrix}, \quad (4.7)$$

where $f''_{ij} = \frac{\partial^2 \chi_i}{\partial r_i \partial r_j} \forall i, j \in V$.

Hence, for all r_i such that $\alpha_i, \pi_i > 0; \forall i \in V$. This is then given by:

$$f''_{i,j} = \begin{cases} -\frac{\alpha_i}{(r_i + 1)^2} < 0 & \text{if } i = j; \forall i, j \in V \\ 0 & \text{if } i \neq j; \forall i, j \in V \end{cases} \quad (4.8)$$

$$H_{\Theta_i}(s) = \begin{bmatrix} b''_{11} & b''_{12} & \cdots & b''_{1n} \\ b''_{21} & b''_{22} & \cdots & b''_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b''_{n1} & b''_{n2} & \cdots & b''_{nn} \end{bmatrix}, \quad (4.9)$$

where $b''_{ij} = \frac{\partial^2 \Theta_i}{\partial r_i \partial r_j} \forall i, j \in V$.

$$b''_{i,j} = \begin{cases} -\frac{\alpha_i}{(r_i + 1)^2} - \frac{2\beta_i}{N(r_{in})^3} & \text{if } i = j; \forall i, j \in V \\ -\frac{2\beta_i}{N(r_{in})^3} & \text{if } i \neq j; \forall i, j \in V \end{cases}. \quad (4.10)$$

Proposition: A matrix is negative definite if and only if k leading principle minors alternate in sign with the odd order ones being < 0 and the even order ones being > 0 [142]. Therefore, it is clear that the leading principal minors [142] and [143] of $H_{\chi_i}(s)$ and $H_{\Theta_i}(s)$ are Negative Definite. Thus, the both $\chi_i(r_i, r_{-i})$ and $\Theta_i(r_i, r_{-i})$ are strictly concave in $S_i; \forall i \in V$.

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

According to [144], the above conditions (in *Theorem 4.2.1* and *4.2.2*) are enough to prove that both games $G1$ and $G2$ have at least one pure strategy Nash equilibrium.

Theorem 4.2.3 *Given VANETs congestion games $G1 = (V, (S_i)_{i \in V}, (\chi_i)_{i \in V})$ and $G2 = (V, (S_i)_{i \in V}, (\Theta_i)_{i \in V})$, where every strategy set S_i is compact and convex, $\chi_i(r_i, r_{-i})$ and $\Theta_i(r_i, r_{-i})$ are strictly concave and continuous in S_i . Let $\mathbf{q} = [q_1, q_2, \dots, q_n]$ be an arbitrary vector of fixed non-negative parameters and if the Diagonal Strict Concavity (DSC) property holds true. Then both games $G1$ and $G2$ have a unique pure-strategy Nash equilibrium [139].*

Proposition: Following a similar procedure (in Rosen's *theorem 4.2.2*) [139]. Let $q = (q_1, q_2, \dots, q_n)$ be an arbitrary vector of fixed positive parameters and the weighted non-negative sum of the utility functions $\chi_i(r_i, r_{-i})$ and $\Theta_i(r_i, r_{-i})$; $\forall i \in V$ are given by

$$\psi_{\chi_i}(r_i, r_{-i}; q_i) = \sum_{i=1}^n q_i \chi_i(r_i, r_{-i}), \quad (4.11)$$

$$\psi_{\Theta_i}(r_i, r_{-i}; q_i) = \sum_{i=1}^n q_i \Theta_i(r_i, r_{-i}). \quad (4.12)$$

Then the pseudo-gradient that is an important property of $\psi_{\chi_i}(r_i, r_{-i}; q_i)$ and $\psi_{\Theta_i}(r_i, r_{-i}; q_i)$ is estimated by:

$$g_{\chi_i}(r_i, r_{-i}; q) = \begin{bmatrix} q_1 \nabla \chi_1(r_1, r_{-1}) \\ q_2 \nabla \chi_2(r_2, r_{-2}) \\ \vdots \\ q_n \nabla \chi_n(r_n, r_{-n}) \end{bmatrix}, \quad (4.13)$$

$$g_{\Theta_i}(r_i, r_{-i}; q) = \begin{bmatrix} q_1 \nabla \Theta_1(r_1, r_{-1}) \\ q_2 \nabla \Theta_2(r_2, r_{-2}) \\ \vdots \\ q_n \nabla \Theta_n(r_n, r_{-n}) \end{bmatrix} \quad (4.14)$$

The functions $\psi_{\chi_i}(r_i, r_{-i}; q_i)$ and $\psi_{\Theta_i}(r_i, r_{-i}; q_i)$ are called diagonally strictly concave in every $r \in S$ for constant $q \geq 0$ if for every $r^0, r^1 \in S$ we have

$$(r^1 - r^0) \psi_{\chi_i}(r^0, q_i) + (r^0 - r^1) \psi_{\chi_i}(r^1, q_i) \geq 0. \quad (4.15)$$

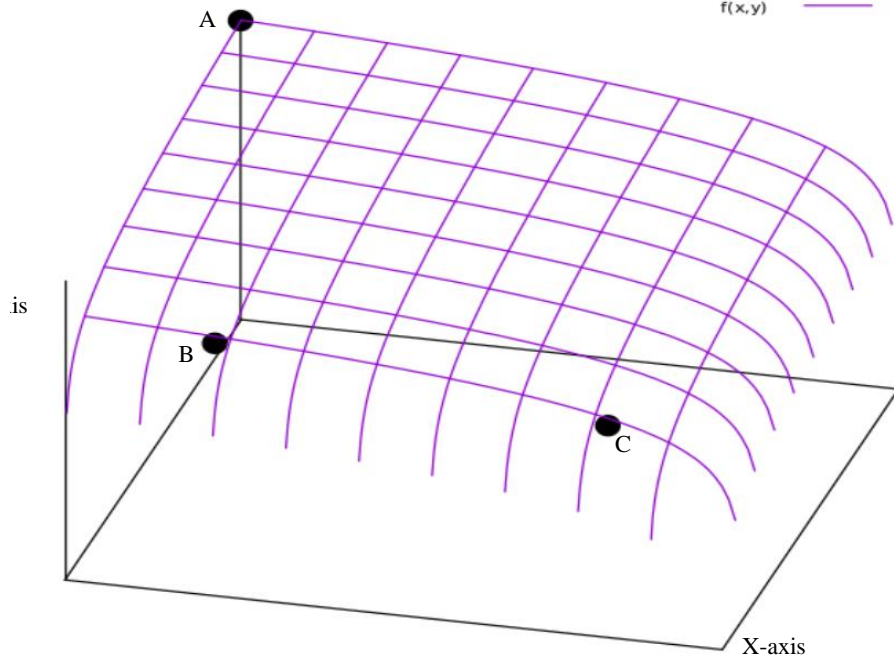


Figure 4.1: Diagonal Strict Concavity [139].

$$(r^1 - r^0)\psi_{\Theta_i}(r^0, q_i) + (r^0 - r^1)\psi_{\Theta_i}(r^1, q_i) \geq 0. \quad (4.16)$$

Therefore, in order to find a maximum value of $\psi_{\chi_i}(r_i, r_{-i}; q_i)$ and $\psi_{\Theta_i}(r_i, r_{-i}; q_i)$, ψ_{χ_i} and ψ_{Θ_i} are needed to be diagonally strictly concave. Then by starting at any point and just following the gradient of $\nabla\chi_i(r_i, r_{-i})$ and $\nabla\Theta_i(r_i, r_{-i})$ as in Figure (4.1) until the maximum is found and no matter where function is started, it will always end up at the same point (Start at the lower black points and follow the direction of the gradient (the direction of the steepest ascent)).

Here, let the gradient of $\nabla\chi_i(r_i, r_{-i}) = \frac{\alpha_i}{r_i + 1} - \frac{\pi_i}{p_i}$ and $\nabla\Theta_i(r_i, r_{-i}) = \frac{\alpha_i}{r_i + 1} + \frac{\beta_i}{N(r_{in})^2} - \frac{\pi_i}{p_i}$, $\forall i \in V$. Then, the Jacobian matrix ($G_{\chi_i}(r_i, r_{-i}; q)$ and $G_{\Theta_i}(r_i, r_{-i}; q)$) with respect to r_i

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

of $g_{\chi_i}(r_i, r_{-i}; q)$ and $g_{\Theta_i}(r_i, r_{-i}; q)$, receptively are given as follows:

$$G_{\chi_i}(r_i, r_{-i}; q) = \begin{bmatrix} E_{11} & E_{12} & \dots & E_{1n} \\ E_{21} & E_{22} & \dots & E_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ E_{n1} & E_{n2} & \dots & E_{nn} \end{bmatrix}, \quad (4.17)$$

where $E_{i,j} = q_i f''_{i,j}$; $\forall i, j \in V$.

$$G_{\Theta_i}(r_i, r_{-i}; q) = \begin{bmatrix} M_{11} & M_{12} & \dots & M_{1n} \\ M_{21} & M_{22} & \dots & M_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ M_{n1} & M_{n2} & \dots & M_{nn} \end{bmatrix} \quad (4.18)$$

where $M_{i,j} = q_i b''_{i,j}$; $\forall i, j \in V$.

Following a similar procedure (in Rosen's *theorem 4.2.2*) [139] is that the symmetric matrix $[G_{\chi_i}(r_i, r_{-i}; q) + G_{\chi_i}^T(r_i, r_{-i}; q)]$ and $[G_{\Theta_i}(r_i, r_{-i}; q) + G_{\Theta_i}^T(r_i, r_{-i}; q)]$ be negative definite for all $r_i, r_{-i} \in S$. Then, functions $\psi_{\chi_i}(r_i, r_{-i}; r)$ and $\psi_{\Theta_i}(r_i, r_{-i}; r)$ are both diagonally strictly concave. Hence, Based on Rosen's Theorem (Theorem 2) [139], the VANET congestion games $G1$ and $G2$ have a unique pure strategy Nash equilibrium.

A square matrix is said to be diagonally dominant if for every row of the matrix, the magnitude of the diagonal entry in a row is larger than or equal to the sum of the magnitudes of all the other (non-diagonal) entries in that row. A matrix G is said diagonally dominant if $|a_{ii}| \geq \sum_{i \neq j} |a_{ij}|$, $\forall i, j \in V$.

4.3 The Solution Calculation of the VANET Game

his section describes how the solution to the VANET game that was formulated above can be found. Two solutions are presented here: Firstly, the solution from the initial work reported in [19] that is solved using Lagrangian multipliers. Secondly, a solution based on the Newton-Raphson optimization method. Note, this second method was required due to the extra complexity caused by adding the contention delay to the final utility function proposed in this paper.

4.3.1 GTACC approach implementation

This chapter proposes a new channel congestion alleviation approach that is called GTACC which is specially tailored for VANETs. In the previous section the VANET game and the vehicle utility function have been formulated. The optimal game solution (r_i^*) needs to be estimated where the vehicles (players) select a strategy that improves their utility function. The player utility function can be optimized as a constrained non-linear programming model:

$$\begin{aligned}
 & \underset{r_i \in S_i}{\text{maximize}} && \chi_i(r_i, r_{-i}), \\
 & \text{subject to} && \sum_{i=1}^n r_i \leq C, \\
 & && 0 \leq r_i \leq r_i^{max}, \forall i \in V.
 \end{aligned} \tag{4.19}$$

Here, C is the Maximum Data Load (MDL), that avoids channel congestion.

To solve the problem (4.19), let $\mathcal{L}_i(r_i, \lambda_i, \xi_i)$ represent the Lagrangian function of player i as follows:

$$\mathcal{L}_i = \chi_i(r_i, r_{-i}) + \lambda_i(C - \sum_{i=1}^n r_i) + \xi_i(r_i^{max} - r_i). \tag{4.20}$$

Here, λ_i and ξ_i are the Lagrange multipliers. The λ_i represent the prices connected with the channel capacity constraint that other vehicles need to pay as a penalty per broadcasting traffic information and reserving the shared communication channel of the vehicle v_i . The prices show the channel congestion situation of the wireless channel connected with a vehicle. The ξ_i associated with the second constraint ensures that the sending rate of the vehicle to be within the range of $[0, r_i^{max}]$ values. Most of the previous works piggybacked the λ_i or prices in a beacon which added an extra overhead on the wireless channel. However, in this thesis, the procedure of piggybacked the λ_i or prices in a beacon has been avoided by periodically comparing the channel usage level with a threshold value individually by each vehicle for every CCH interval as follows:

$$\text{Channel Usage Level} = \frac{\sum_n (D_{BUSY} + D_{AIFS} + \overline{D_{Backoff}})}{D_{CCH}}. \tag{4.21}$$

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

The channel usage level represents the measured channel busy time of n packets sensed by a vehicle in one CCH interval. D_{BUSY} shows the channel busy duration registered by the Channel Clear Assessment (CCA) module for every sensed message. D_{AIFS} is the Arbitrary Inter-Frame Space (AIFS) which represents a fixed period of time that every vehicle needs to listen for the wireless channel before transmitting information. $\overline{D_{Backoff}}$ is the backoff time that each vehicle recorded when the channel is busy. D_{CCH} is one CCH interval duration which is normally 50ms in the WAVE system.

The KKT conditions of vehicle (player) v_i to obtain optimal solution are as follows:

$$\begin{aligned} \lambda_i, \xi_i &\geq 0, \\ r_i &\geq 0, \\ r_i^{max} - r_i &\geq 0, \\ \nabla_{r_i} \chi_i(r_i, r_{-i}) + \lambda_i \nabla_{r_i} (C - \sum_{i=1}^n r_i) + \xi_i \nabla_{r_i} (r_i^{max} - r_i) &= 0, \\ \lambda_i (C - \sum_{i=1}^n r_i), \xi_i (r_i^{max} - r_i) &= 0. \end{aligned}$$

The problem in (4.20) has three unknowns (r_i , λ_i and ξ_i). In order to solve the problem, three cases are considered based on complementarity conditions:

Case 1: $r_i = 0$ and $\xi_i = 0$:

$$\begin{aligned} \alpha_i - \frac{\pi_i}{p_i} + \lambda_i &= 0 \\ \lambda_i &= \frac{\pi_i}{p_i} - \alpha_i \end{aligned}$$

The solution $r_i = 0$ is feasible, if the condition ($\lambda_i > 0$) holds and it is as follows:

$$\frac{\pi_i}{p_i} \geq \alpha_i \quad \text{condition 1}$$

Case 2: $r_i = r_i^{max}$ and $\lambda_i = 0$:

$$\begin{aligned} 4 \frac{\alpha_i}{r_i^{max} + 1} - \frac{\pi_i}{p_i} - \xi_i &= 0 \\ \xi_i &= \frac{\alpha_i}{r_i^{max} + 1} - \frac{\pi_i}{p_i} \end{aligned}$$

4.3 The Solution Calculation of the VANET Game

The solution $r_i = r_i^{max}$ is feasible, if the condition ($\xi_i > 0$) holds and it is as follows:

$$\frac{\pi_i}{p_i} \leq \frac{\alpha_i}{r_i^{max} + 1} \quad \text{condition 2}$$

Case 3: $\lambda_i = 0$, $\xi_i = 0$ and ($0 < r_i < r_i^{max}$)

$$\frac{\alpha_i}{r_i + 1} - \frac{\pi_i}{p_i} = 0$$

$$r_i = \frac{\alpha_i p_i}{\pi_i} - 1.$$

Hence, the optimal data rate (r_i^*) for player v_i ; $\forall i \in V$

$$r_i^* = \begin{cases} \frac{\alpha_i p_i}{\pi_i} - 1 & \text{otherwise} \\ r_i^{max} & \text{if condition 1} \\ 0 & \text{if condition 2} \end{cases} \quad (4.22)$$

where condition 1 and condition 2 are as follows:

$$\frac{\pi_i}{p_i} \leq \frac{\alpha_i}{r_i^{max} + 1} \quad (4.23)$$

$$\frac{\pi_i}{p_i} \geq \alpha_i. \quad (4.24)$$

4.3.2 NCGACC Approach Implementation

This work proposes using the Newton-Raphson method [145] to optimize the problem given in (4.25) due to the formulated utility function being unable to be solved via Lagrange multiplier and KKT conditions.

$$\begin{aligned} & \underset{r_i \in S_i}{\text{maximize}} && \Theta_i(r_i, r_{-i}) \\ & \text{subject to} && \sum_{i=1}^n r_i \leq C \\ & && 0 \leq r_i \leq r_i^{max}, \forall i \in V. \end{aligned} \quad (4.25)$$

The Newton-Raphson method is a formula for numerically estimating function roots. Once the utility function is differentiable, the method takes the derivative of the utility function and sets it to zero. Then, if the function satisfies the as-

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

assumptions made in the derivation of the utility function and the initial assumption is close, then a better approximation $r_{i,k+1}$ is achieved. The main characteristics of the Newton-Raphson method are fast convergence to the root quadratic and easy conversion to multiple dimensions. Algorithm 1 describes the procedure of finding vehicles optimal data rate r_i^* in VANETs. The developed approach has been implemented on the top of the application layer. The channel usage level at the MAC layer has been used as a parameter in order to monitor the channel congestion and notify the application layer to adjust the sending rate of the traffic information.

Algorithm 2 Newton-Raphson method.

- 1: *Initialization:*
Set variables α_i , β_i and π_i
Set r^{max}
Set r_0
 - 2: $k = 0$
 - 3: Find the value r_i^* of r_i that maximizes $\Theta_i(r_{i,k}, r_{-i,k})$
 - 4: **while** $\Theta'_i(r_{i,k}, r_{-i,k}) > \text{tolerance}$
 do
 $r_{i,k+1} \leftarrow r_{i,k} - \frac{\Theta_i(r_{i,k}, r_{-i,k})}{\Theta'_i(r_{i,k}, r_{-i,k})}$
 $r_{i,k+1}^* \leftarrow r_{i,k+1}$
 $k \leftarrow k + 1$
 - 5: **Return** $r_{i,k+1}^*$
-

In VANET systems, vehicles or RSUs broadcast their data to the nearest vehicles or RSUs in their transmission range. The congestion in the wireless channel happens when many vehicles start to periodically send many messages (CAMs and DENMs) at the same time or relay a large volume of data across the network. Here, every vehicle or RSU will check the congestion conditions periodically by comparing the channel usage with a threshold value as in [81]. Once the congestion is detected, the vehicles adapt their data rate as in Algorithm 1. Figure 4.2 summarizes the steps of the proposed NCGACC approach.

4.4 Performance Evaluation of GTACC

The proposed method has been tested and evaluated through the vehicular network simulator Veins [146] which integrates the Simulator for Urban MObility

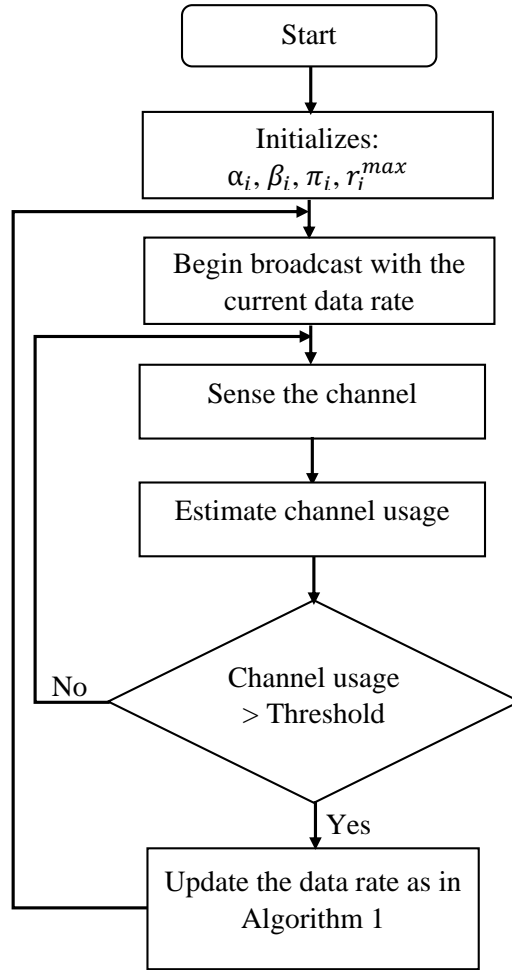


Figure 4.2: The flow chart of congestion control in VANET

(SUMO) [127] with the network simulator OMNeT++ [147] to manage the mobility of vehicles and the communication between V2V or V2I communication systems. Ten independent Monte Carlo simulations were conducted and the mean results reported.

The proposed algorithm has been implemented for differing numbers of vehicles, with the transmission data rate being optimized in each scenario. The GTACC has been compared with the CSMA/CA that is originally implemented in the WAVE protocol [148]. The GTACC approach has been implemented based on CCH of MAC layer in WAVE protocol. This is in order to mitigate the congestion generated due to the continuous transfer of safety messages. In this thesis, initial results have been provided based on a single stretch of road as a proof of

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

concept. Therefore, free space path loss has been used and effects such as shadow fading and scattering have not yet been considered. Such effect could be included in future work.

Long Term Evolution-Vehicle (LTE-V) sidelink is another VANET protocol for supporting V2V and V2I communication systems. However, it has a different mechanism to transmit the safety messages as compared to WAVE protocol. Studies exist which have addressed the performance comparison between these two protocols. For example, [149] shows that when transmissions of periodic cooperative awareness messages are performed by LTE, the capacity of the network is limited by the downlink data channel. In turn, [150] argues that the uplink data channel is a bottleneck of the LTE network for the intelligent transport systems use cases. These two studies have shown that the wireless channel congestion problem is generated when there is a large number of vehicles inside the base station transmission range. Thus, the GTACC approach can equally be applied to LTE-V side-link network to alleviate the channel congestion as a future work and similar performance patterns are expected to be obtained.

Four different performance measures have been considered in this performance evaluation:

- **Average throughput (mbps):** The total number of received packets at all vehicles.
- **Average delay (ms):** The time needed to deliver a packet between the sender and receiver.
- **Packet loss (Number of packets):** The number of packets are lost in channel or MAC buffer.
- **Channel busy time (s):** Indicates the wireless channel busy time within a given interval.

Table 4.1 shows the parameters that have been used in the simulation, where the vehicles speed have been chosen by the designer based on the the authors' experience of the problem and using U.K. road laws as a guide.

Table 4.1: Configuration parameters for the implemented example

Simulation parameters	Value
Map dimension	1.0 km
Vehicles speed	2.5-34 m/s
Number of vehicles	50, 70, 90, 110, 130, 150
Simulation time	200 s
MAC/PHY	IEEE 802.11p
Transmission range	300-1000 m
Transmission rate	3-27 Mbps
Safety messages data rate	10 packet/s
α_i	20
π_i	2
w_1	0.7
w_2	0.3

4.4.1 Parameters Selection of the Game Approach

This section shows the effect of selecting different values of (α_i and π_i) on the beacon rate and Channel Busy Ratio (CBR). Here, a high way scenario with 150 vehicles has been tested and evaluated in order to select the desired parameters that satisfy the system requirements. Figures 4.3 and 4.4 show the effect of changing weights in the cost function on beacon rate and CBR. For example, when π_i is constant and equal to 2.0, and the α_i has different values of (20.0, 25.0 and 30.0), respectively. It is clear from the Figures 4.3 and 4.4 that increasing the values of α_i will increase the vehicle data rate and that will be at the expense of using high bandwidth. On the other hand, increasing the value of π_i will decreasing the sending rate of vehicles which will decrease the CBR due to use lower data rate as shown in Figures 4.5 and 4.6. It is clear that by increasing value of π_i the data rate and the CBR will decrease and vice versa. In this thesis, these values have been chosen in order to reach trade-off among weights and satisfy the congestion requirements.

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

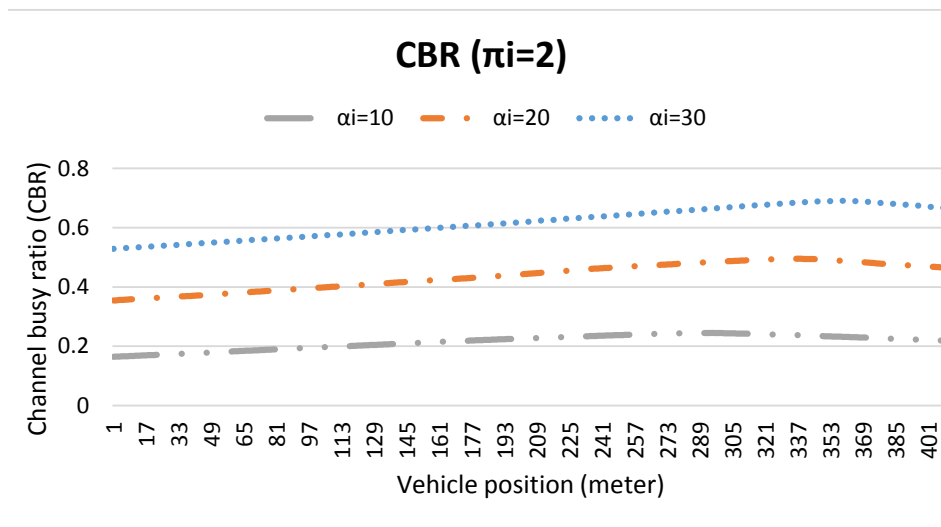


Figure 4.3: α_i vs CBR.

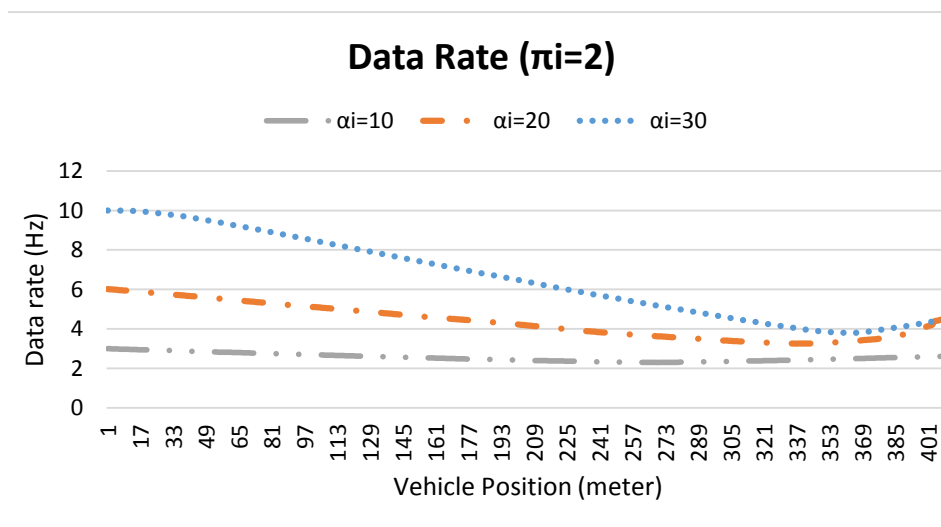


Figure 4.4: α_i vs data rate.

4.4.2 Highway Simulation Scenario

A four lane road with traffic flowing in one direction has been implemented in SUMO to evaluate and test the proposed method as shown in Figure 4.7.

Figure 4.8 shows the total average throughput obtained by GTACC and CSMA/CA, respectively. It is obvious that the average throughput increases with

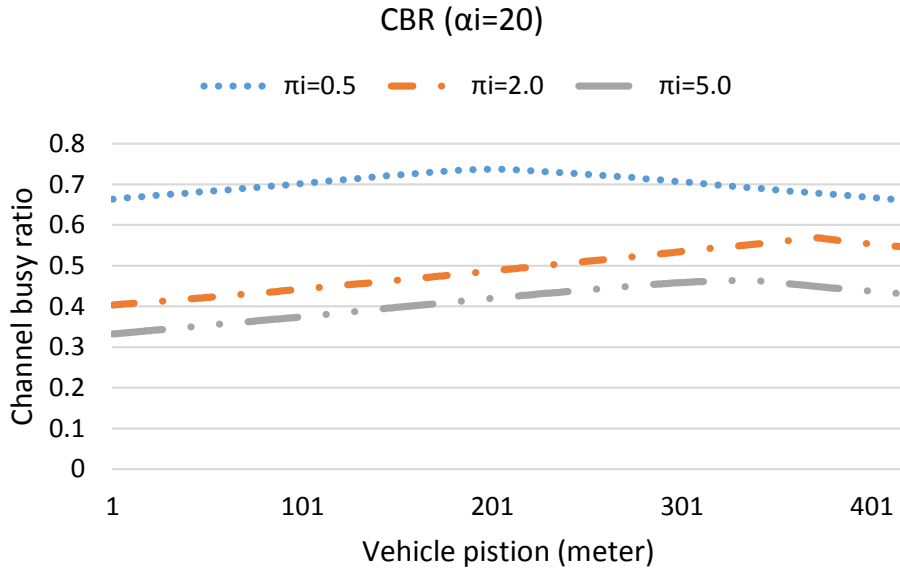


Figure 4.5: π_i vs CBR.

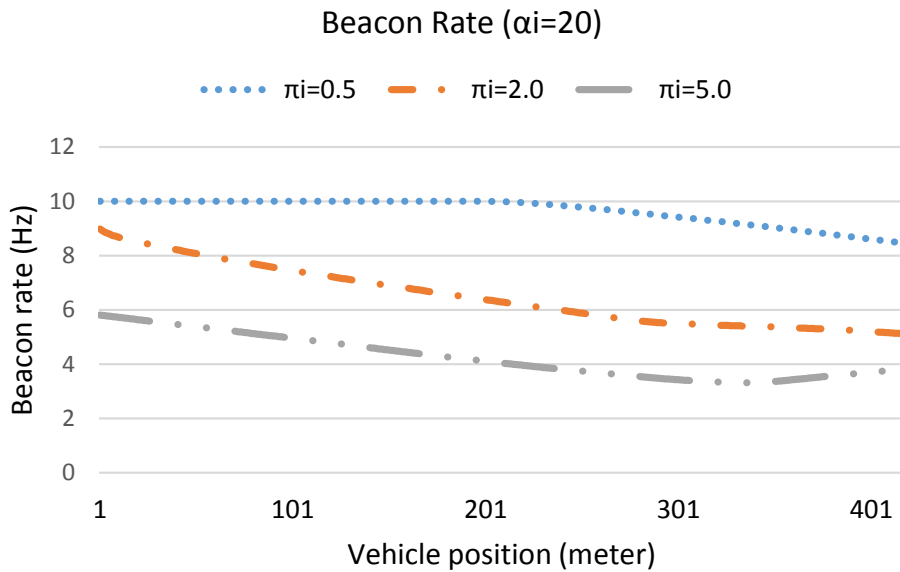


Figure 4.6: π_i vs data rate.

increasing numbers of vehicles. It is also clear that the GTACC method has significantly improved the average throughput as compared to the CSMA/CA. The reason is that the GTACC adapts the sending rate of vehicles based on their chosen optimal value as well as considering message and vehicle priorities once the congestion occurs. On the other hand, the CSMA/CA does not have data

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

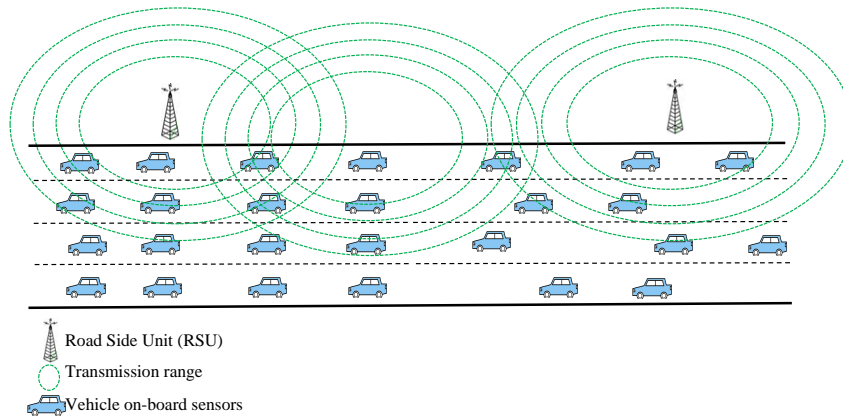


Figure 4.7: A Example scenario considered in SUMO.

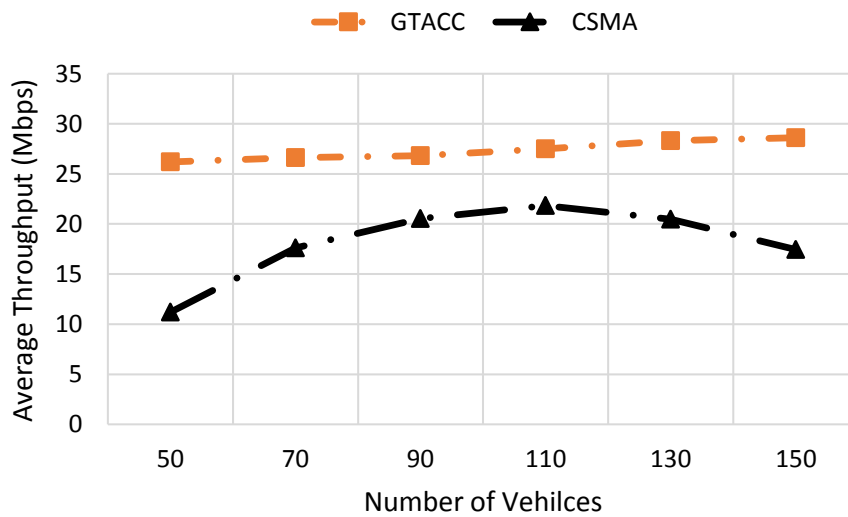


Figure 4.8: Total average throughput

rate adaptation mechanism when the congestion in the wireless channel occurs. This leads to many messages being sent through the network at a high data rate, which in turn leads to collision and congestion in wireless channel causing packet loss and thus reduced throughput.

Figure 4.9 depicts the variation of the average delay with the number of vehicles. It is clear when the number of vehicles increases the average delay increases. The results show that the delay in GTACC method is significantly less than the CSMA/CA and there is also not a sharp increase in the average delay when there is an increase in the number of vehicles. This is because the data rate has been tuned to obtain the optimal sending value, which in turn minimizes the delay in

4.4 Performance Evaluation of GTACC

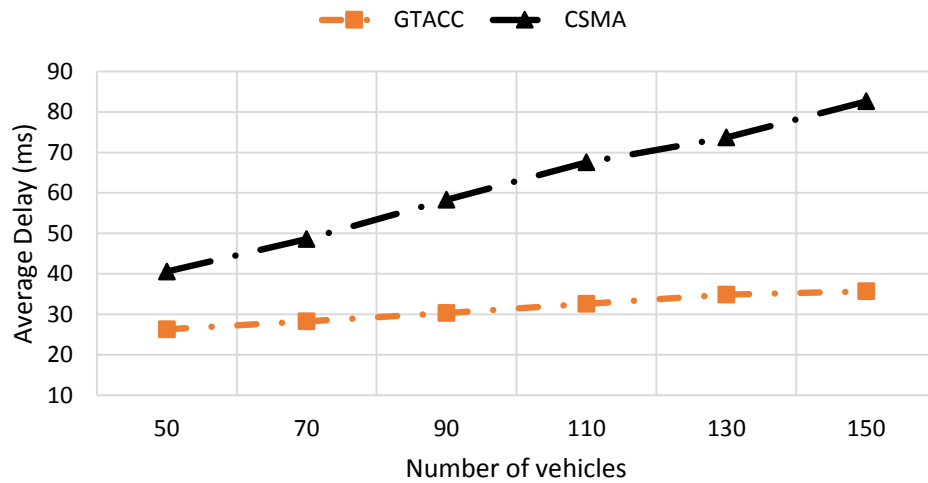


Figure 4.9: Total average delay

receiving the packets.

Figure 4.10 illustrates the total number of lost packets in the network due to the congestion in the wireless channel. It is obvious that the number of lost packets in GTACC is less than the CSMA/CA. This is due to using an adaptive sending rate which helps to mitigate the congestion in the wireless channel. This decreases the number of lost packets, regardless of the number of vehicles being considered. However, the CSMA/CA has many lost packets due to sending messages at a high unoptimized data rate which leads to a collision in the transmitted data and congestion in the wireless channel.

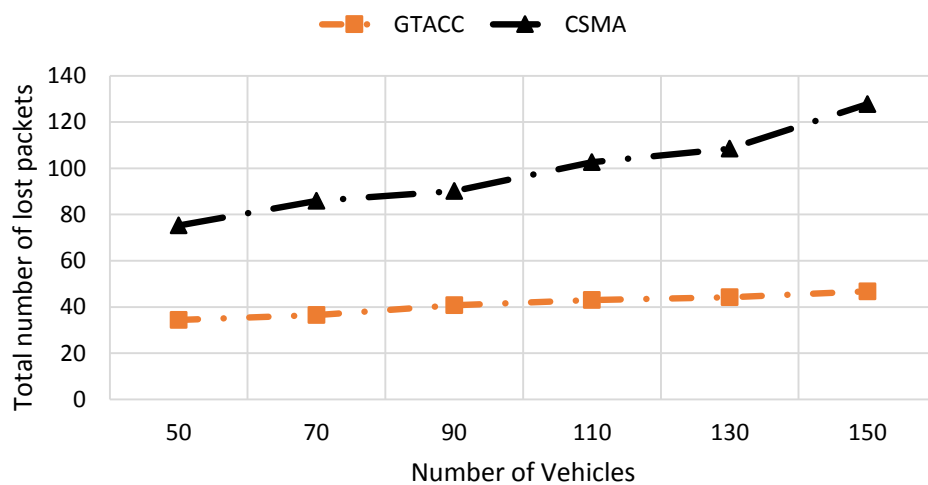


Figure 4.10: Total number of lost packets

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

Figure 4.11 depicts the total channel busy time from GTACC and CSMA/CA, respectively. The effect of sending at a high data rate on channel occupancy time is evident. It is clear that the CSMA/CA has a higher channel busy time. This is due to the contention between vehicles trying to send messages at a high data rate without considering the available resources. On the other hand, the GTACC has better channel busy time as compared to CSMA/CA. This is due to tuning the data rate to obtain the optimal sending rate for each vehicle individually.

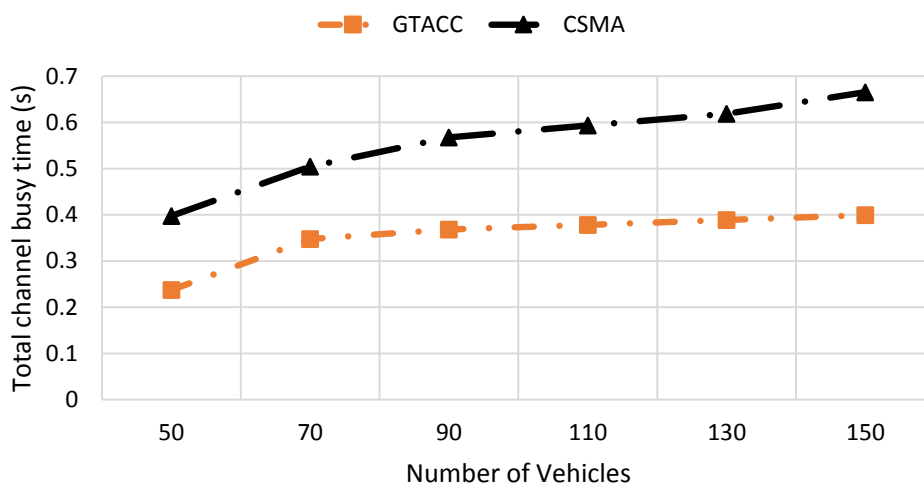


Figure 4.11: Total channel busy time

4.4.3 Urban Simulation Scenario

Here, an urban road with two-lane has been designed in Veins to estimate the performance of the proposed strategy. Figure 4.12 depicts the urban scenario that is implemented in Veins.

Figure 4.13 describes the significance of the number of vehicles on the average throughput. It is obvious that GTACC has a better throughput as the number of connected vehicles increases unlike the throughput obtained by WAVE that has been affected by increasing the number of connected vehicles in the vehicular network. This is due to the lack of the adaptation mechanism in WAVE which assists to diminish the congestion and number of lost messages. This assists to increase the number of received packets at the destination nodes.

Figure 4.14 illustrates the variances of average delay results recorded during the simulation time by the WAVE and GTACC, respectively. It is expected that

4.4 Performance Evaluation of GTACC

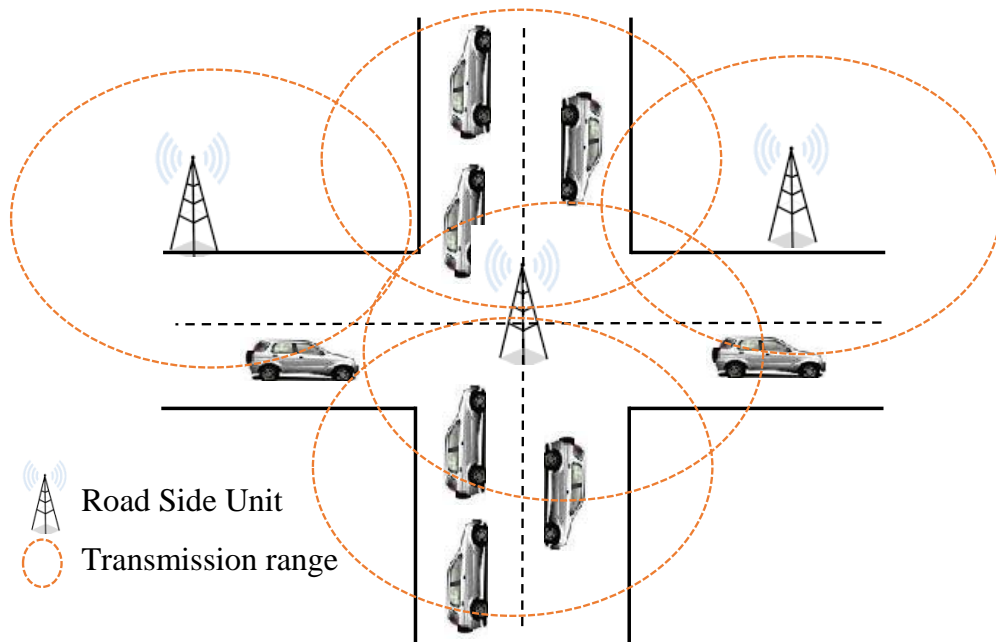


Figure 4.12: The considered urban scenario of the evaluated approaches

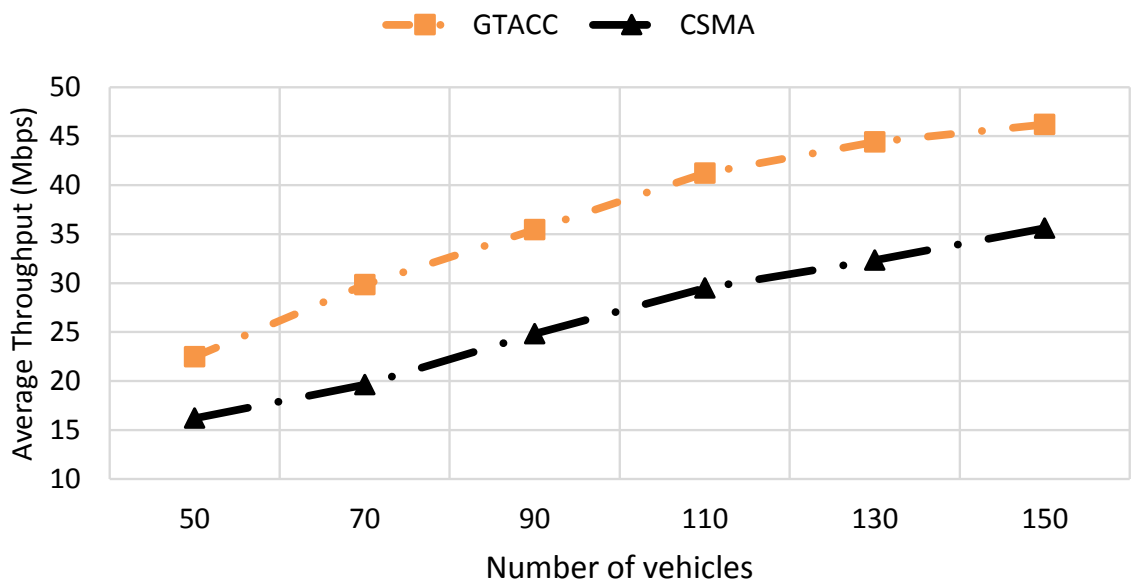


Figure 4.13: Average throughput of evaluated approaches in the urban scenario

the increasing number of communicated vehicles in a dense environment affect the delay. It is clear from Figure 4.14 that GTACC has less delay as compared to the WAVE. This is because of WAVE broadcast messages at a maximum value

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

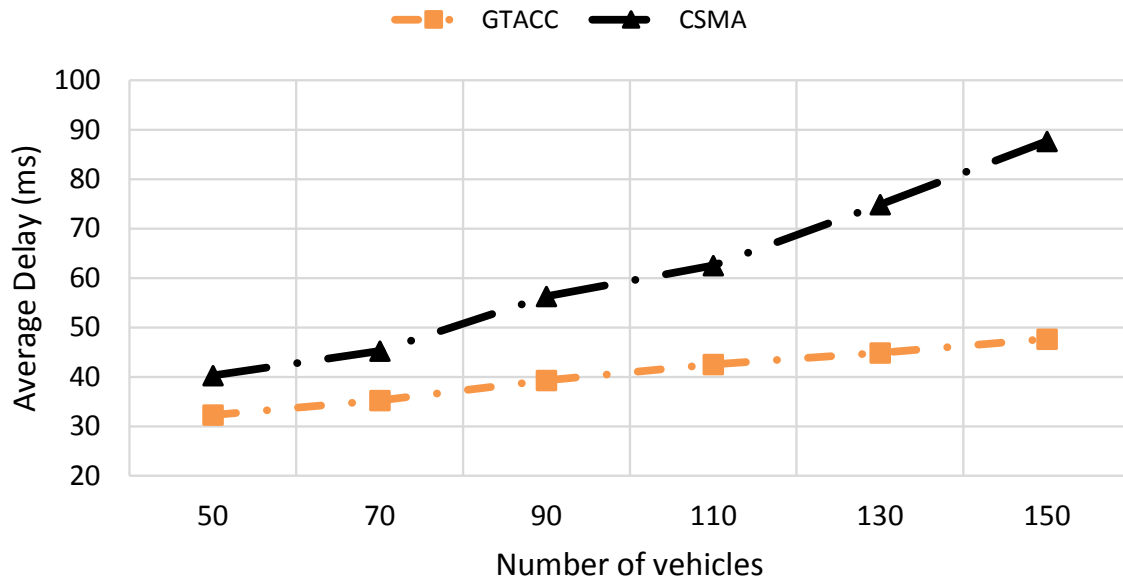


Figure 4.14: Average delay of evaluated approaches in the urban scenario

without considering buffer-overflow and the congestion in the wireless channel which contributes to increasing of the recorded delay values.

Figure 4.15 describes the number of packets lost collected by WAVE and GTACC, respectively. This figure has similar patterns as in figure when the number of vehicles increases the number of packets lost increases due to congestion in wireless channel and competition among the nodes to reserve the channel. It is clear that the GTACC has fewer packets lost as compared to the WAVE due to the adaptation approach which helped to reduce the congestion by selecting the optimal messages rate generation of each vehicle in the network.

Figure 4.16 shows the recorded results of the channel busy time during the simulation scenario for both WAVE and GTACC. The channel busy time increases with increasing the number of nodes desire to access the channel. It is obvious from the Figure 4.16 that the WAVE has worse channel busy time as compared to the GTACC due to the lack of the adaptation mechanism of messages rate and broadcast message at high frequencies which leads to increase the congestion in the wireless channel.

4.4 Performance Evaluation of GTACC

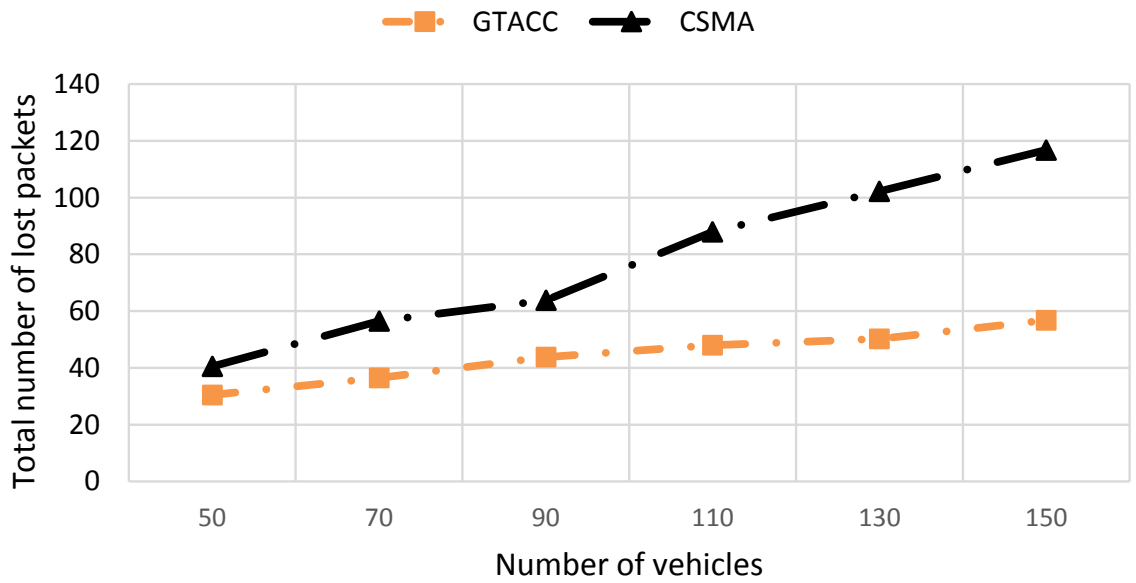


Figure 4.15: Packets loss of evaluated approaches in the urban scenario

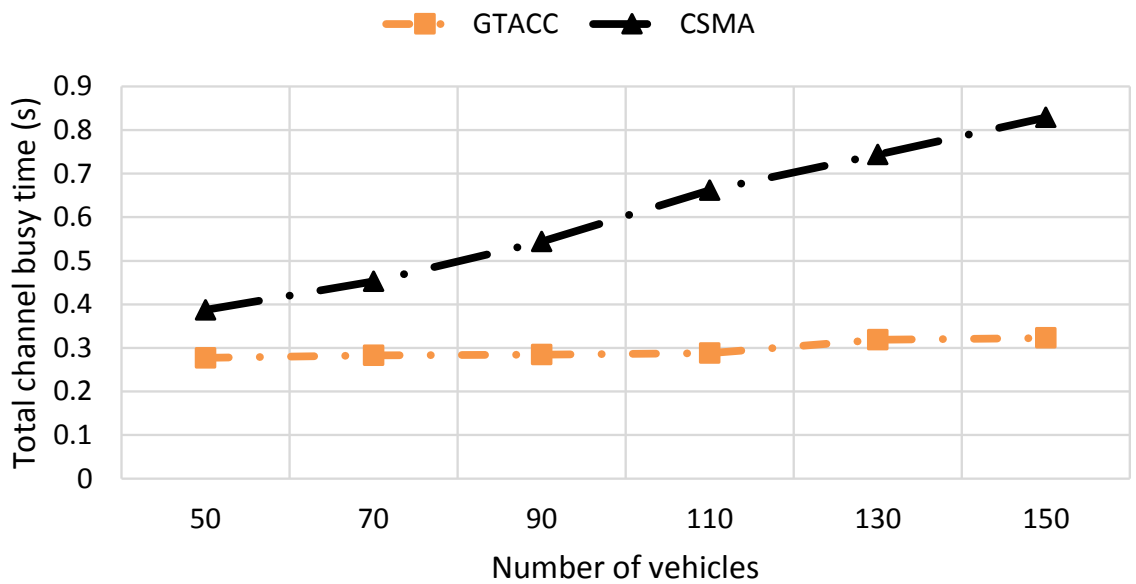


Figure 4.16: The busy time of evaluated approaches in the urban scenario

4.5 Performance Evaluation of NCGACC

4.5.1 An Approach Parameters Selection

This section shows the effect of selecting different values of $(\alpha_i, \beta_i$ and $\pi_i)$ on the beacon rate and CBR. Here, a high way scenario with 150 vehicles has been tested and evaluated in order to select the desired parameters that satisfy the system requirements. Figures 4.17 and 4.18 show the effect of changing weights in the cost function on beacon rate and CBR. For example, when β_i and π_i are constant and equal to 5.0 and 2.0 respectively, and α_i has different values of (10.0, 20.0 and 30.0), respectively. It is clear from the Figures 4.17 and 4.18 that increasing the values of α_i will increase the vehicle data rate and that will be at the expense of using high bandwidth. On the other hand, increasing the value of β_i will increase the price of contention which will decrease the CBR due to use lower data rate as shown in Figures 4.19 and 4.20. Finally, Figure 4.21 and 4.22 show the effect of changing π_i parameter on the data rate and the CBR when α_i and β_i are constant. It is clear that by increasing value of π_i the data rate and the CBR will decrease and vice versa. In this thesis, these values have been chosen in order to reach trade-off among weights and satisfy the congestion requirements.

4.5.2 NCGACC Simulation Results

The proposed approach has been tested and evaluated through the vehicular network simulator Veins [146] which integrates the Simulator for Urban MOBility (SUMO) [127] with the network simulator OMNeT++ [147] to manage the mobility of vehicles and the communication between V2V or V2I communication systems. Two scenarios have been used to test and validate the proposed algorithm (a highway 4-lanes in one direction and an urban street with two intersections). The proposed algorithm has been implemented for differing numbers of vehicles, with the transmission data rate being optimized in each scenario. Ten independent Monte Carlo simulations were conducted and the mean results reported.

Six different performance measures have been considered in this performance evaluation:

4.5 Performance Evaluation of NCGACC

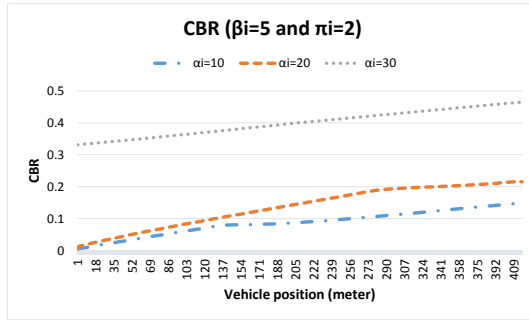


Figure 4.17: α_i vs CBR.

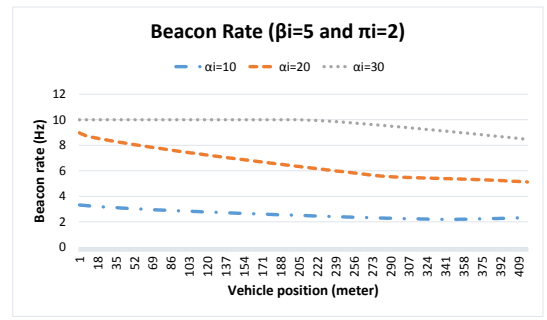


Figure 4.18: α_i vs data rate.

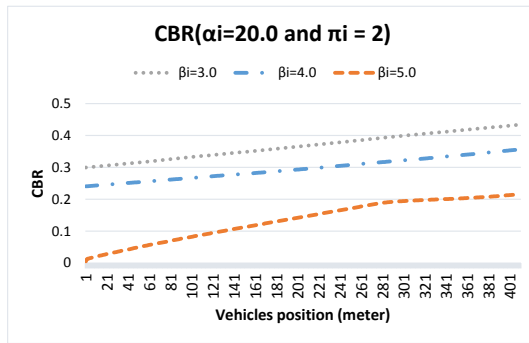


Figure 4.19: β_i vs CBR.

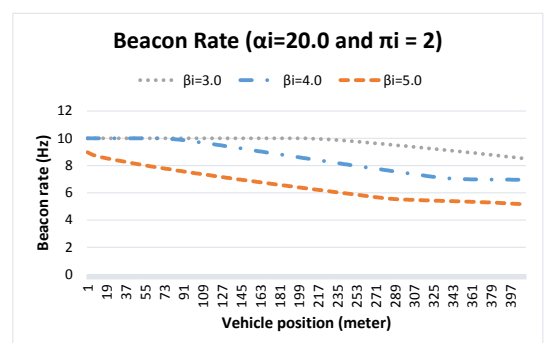


Figure 4.20: β_i vs data rate.

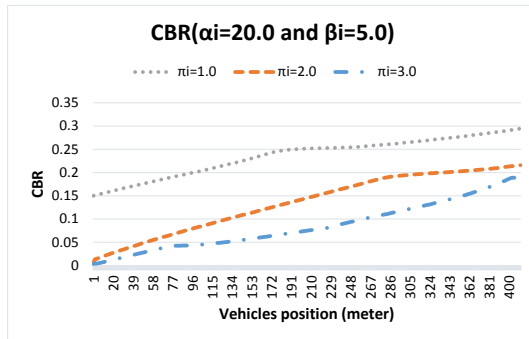


Figure 4.21: π_i vs CBR.

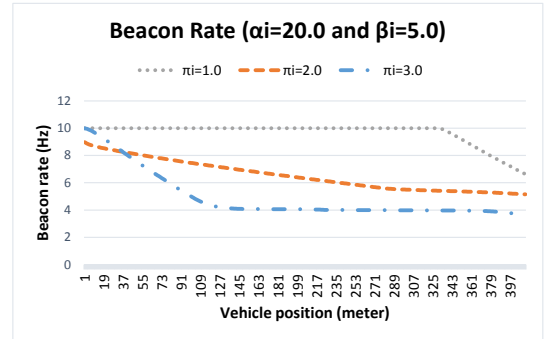


Figure 4.22: π_i vs data rate.

- **Average throughput (mbps):** The total number of received packets at all vehicles.
- **Average delay (ms):** The time needed to deliver a packet between the sender and receiver.
- **Packet loss (Number of packets):** The number of packets are lost in channel or MAC buffer.

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

- **Collision Probability:** Indicates the probability of collision in the wireless channel during sending of messages.
- **Packet Delivery Ratio (PDR) (%)**: It represents the total ratio of the total delivered packets to destination vehicles over total sent packets.
- **Jain's Fairness Index (JFI)**: This metric is used to determine whether nodes or vehicles are receiving a fair share of system resources. The Jain's Fairness Index (JFI) has been estimated similar to [151] as follows:

$$JFI = \frac{\left[\sum_{i=1}^n thp_i \right]^2}{n \sum_{i=1}^n thp_i^2}. \quad (4.26)$$

where thp_i is throughput of vehicle v_i ,

In order to demonstrate the behaviour and performance, the proposed NCGACC approach has been tested over two test scenarios (highway and urban traffic) and compared the initial results reported in [19], NUM and NORAC approaches which are implemented as in [152] and [153], respectively.

4.5.3 A Highway Scenario

In this scenario, a four lane road with traffic flowing in one direction has been implemented in SUMO to evaluate and test the proposed approach as shown in Figure 4.23.

Table 4.2 shows the parameters that have been used in the simulation, where the vehicle speeds have been chosen by the authors based on experience with similar problem instances and using U.K. road laws as a guide. The values of α_i , β_i and π_i in Table 1 are selected to give a suitable trade-off between the optimization criteria considered in the utility function. In essence they decide the relative importance of the terms in the utility function. For example if the value of π_i is increased it means the weighting of priority function is increased, meaning it is given more importance in the optimization. Note, from experience changing these values has impact on the values of the utility function. However,

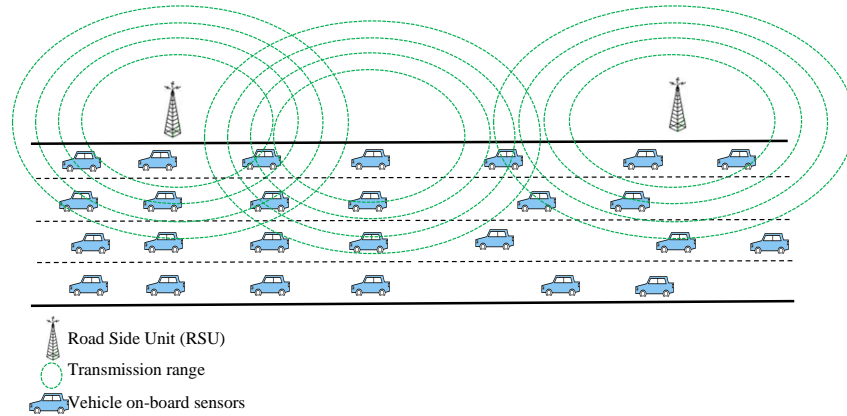


Figure 4.23: A highway scenario considered in SUMO.

the position of the optimal value of the utility function remains constant for a range of parameter values.

Average throughput

Figure 4.24 shows the total average throughput obtained by the three tested algorithms. It is obvious that the average throughput increases with increasing numbers of vehicles. It is clear that the NCGACC approach has significantly improved the average throughput as compared to the GTACC, NUM and NORAC. Using GTACC, NUM, NORAC and NCGACC approaches, the total average throughput for the number of vehicles equal to 150 is 31.61, 27.11, 39.72 and 35.43 mbps in GTACC, NUM, NORAC and NCGACC, respectively. The NCGACC improves the total average throughput by an overall average of 16.55%, 30.49% and 8.8% as compared to GTACC, NUM and NORAC, respectively. The results depict that the proposed approach better than the other methods and is able to achieve a better performance in VANETs. The reason is that the NCGACC adapts the sending rate of vehicles based on its chosen optimal value as well as considering contention delay and vehicle priorities once the congestion occurs. On the other hand, the NUM, GTACC and NORAC do not consider the contention delay in their optimization when the congestion in the wireless channel occurs. This leads to many messages being sent through the network during peak transmission times, which in turn leads to collision and congestion in wireless channel causing packet loss and thus reduced throughput.

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

Table 4.2: Configuration parameters for the implemented examples

Simulation parameters	Value
Map dimension	1000 m highway scenario, and 650 m \times 1000 m urban scenario
Vehicles speed	22-34 m/s highway scenario, and 13-27 m/s urban scenario
Number of vehicles	50, 70, 90, 110, 130, 150
Simulation time	200 s
MAC/PHY	IEEE 802.11p
Transmission range	300-1000 m
Transmission rate	3-27 Mbps
Safety messages data rate	10 packet/s
Maximum iterations	60
α_i	20
β_i	5
π_i	2
w_1	0.7
w_2	0.3

Average delay

Figure 4.25 depicts the variation of the average delay with the number of vehicles. It is clear when the number of vehicles increases the average delay increases. This is because many vehicles will start to compete among each other in order to access the wireless channel and send data at a high rate which leads to a long waiting time and delay in the received information at the destination nodes. The results show that the delay in the NCGACC approach is significantly less than the GTACC, NORAC and NUM approaches. Additionally, the NCGACC does not have a sharp increase in the average delay when there is an increase in the number of vehicles. This is because the data rate has been tuned based on contention delay and vehicles priorities to obtain the optimal sending rates. This

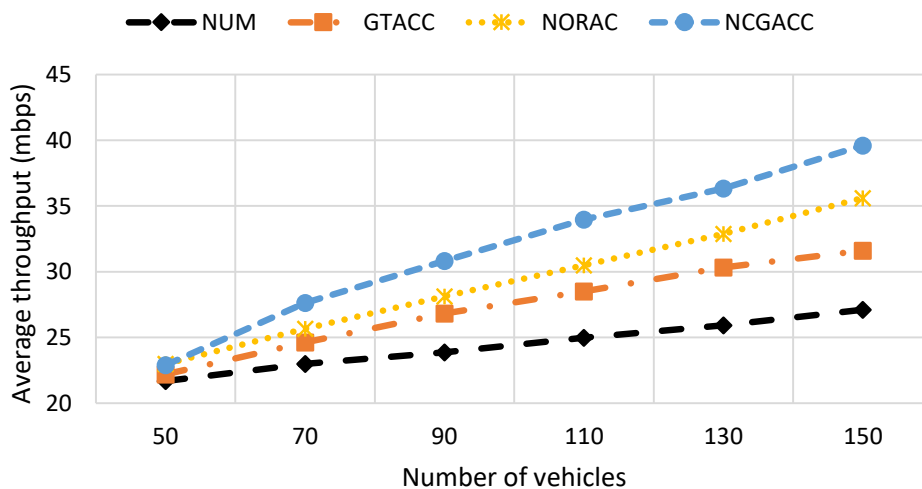


Figure 4.24: Total average throughput in the highway scenario

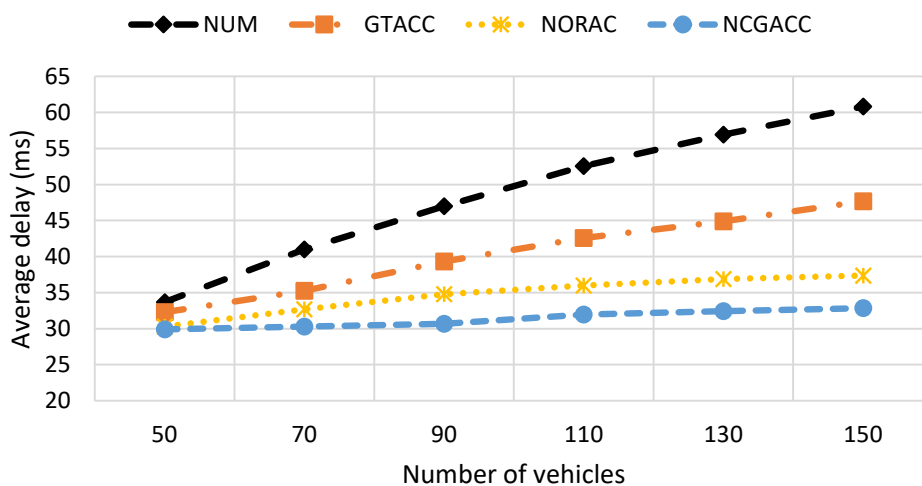


Figure 4.25: Total average delay in the highway scenario

in turn minimizes the delay in receiving the packets.

Number of lost packets

Figure 4.26 illustrates the total number of lost packets in the network due to the congestion in the wireless channel. It is obvious that the number of lost packets in NCGACC is less than the GTACC, NORAC and NUM approaches. This is due to using an adaptive sending rate and choosing the optimal rates by considering contention delay in its utility function which helps to mitigate the congestion in

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

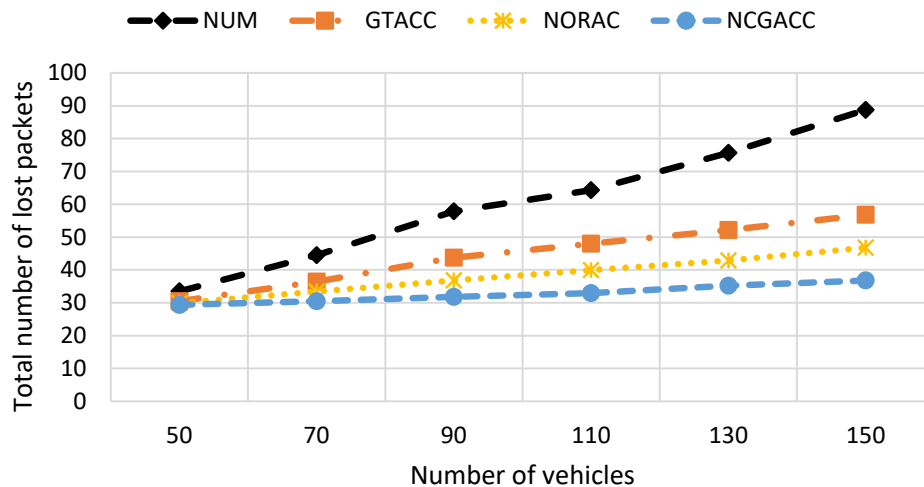


Figure 4.26: Total number of lost packets in the highway scenario

the wireless channel. This decreases the number of lost packets, regardless of the number of vehicles being considered. However, the NUM has many lost packets due to optimizing only non-safety messages, which leads to a collision in the transmitted data and congestion in the wireless channel once the safety messages are generated.

Collision Probability

Figure 4.27 shows the collision probability variations with the number of vehicles. It depicts when the number of vehicles increases the collision probability increases for all tested strategies. However, the NCGACC does not show a significant increase in the collision probability. This is due to the fact that it considers the contention delay parameter as a term in its optimization. Additionally, it can be seen that when 150 vehicles are considered in the simulation the collision avoidance for the proposed NCGACC approach is 0.2. It is worth noting that this is smaller than the value for the comparison approaches even when less vehicles are considered.

Packet Delivery Ratio

Figure 4.28 shows the PDR variations with the number of vehicles. It is clear from Figure 4.28 that the PDR results are directly related to the number of lost packets. The PDR increases by decreasing number of lost packets in the network. It is clear

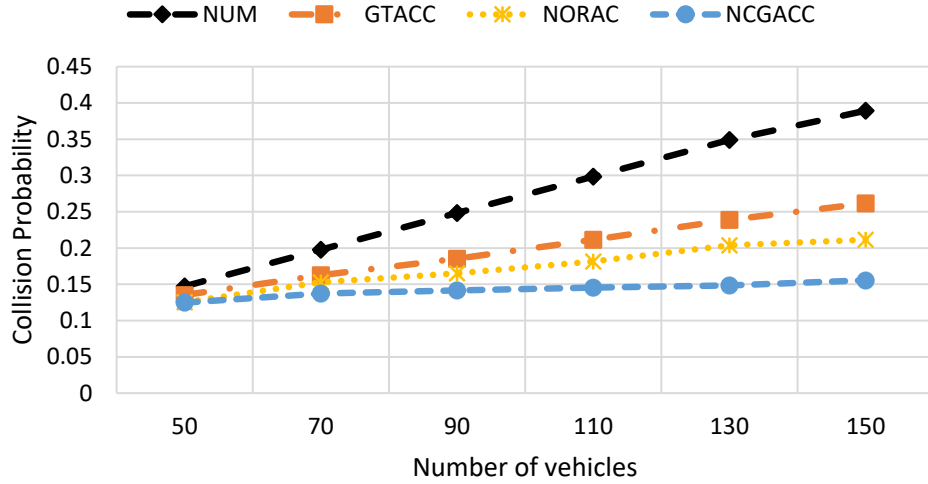


Figure 4.27: Collision probability in the highway scenario

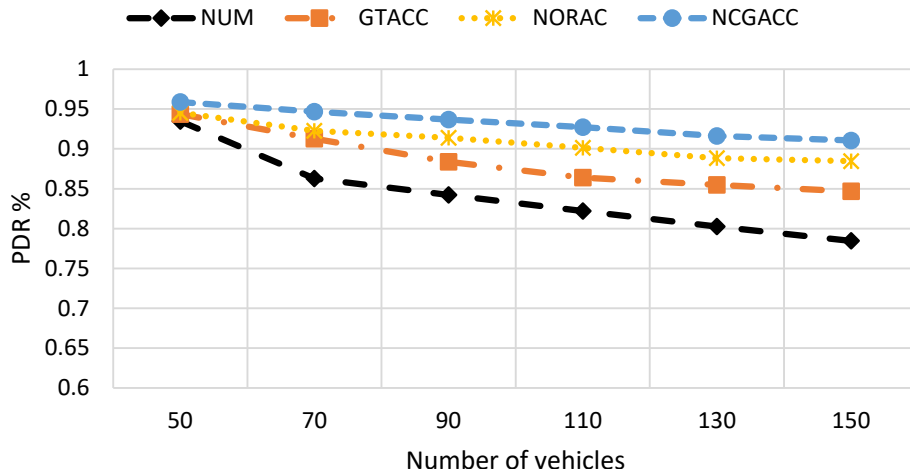


Figure 4.28: Packet delivery ratio in the highway scenario

that the performance of the proposed approach in terms of PDR is better than that of the comparison approaches. This improvement in performance has been achieved by considering three parameters in the optimization process as compared to one and two parameters in NUM, GTACC and NORAC, respectively.

Jain's Fairness Index (JFI)

Figure 4.29 shows the JFI which indicates how fairly the system resources are shared between the vehicles. It is clear that the NCGACC has a better JFI (close to 1) and it is consistent as compared to the GTACC, NORAC and NUM

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

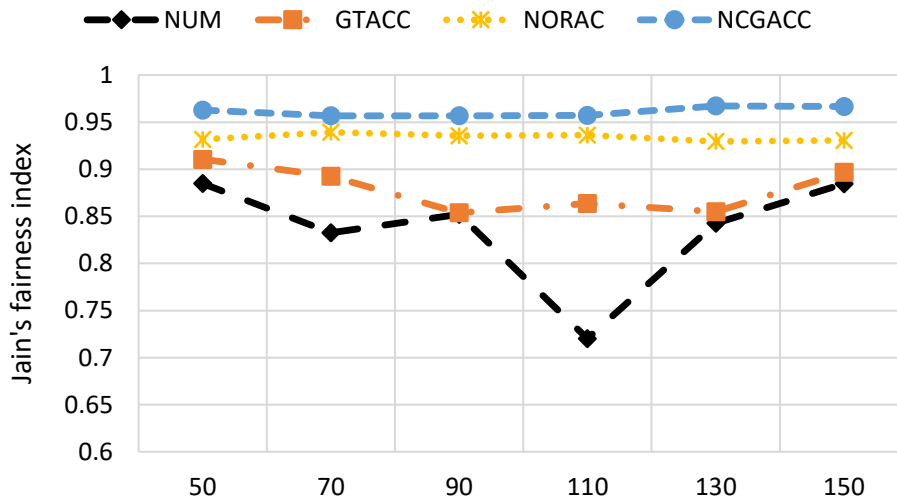


Figure 4.29: Jain's fairness index in the highway scenario

approaches. This indicates that the overall throughput has high fairness allocation among vehicles. On the other hand, the NUM has the lowest JFI among all tested approaches due to the unfair reduction of non-safety messages.

CPU time

Figure 4.30 illustrates the average CPU time that has been estimated for a random number of vehicles for all tested algorithms. It is clear from Figure 4.30 that the GTACC and NUM require less CPU time as compared to NORAC and NCGACC. However, there is not a significant difference in CPU time among all tested approaches. NCGACC has a slight increase in computation time as compared to GTACC and NUM. This is due to the iterative nature of the Newton-Raphson method and the extra term (contention delay) in the utility function that is optimized. However, the increase has not been significant enough to affect the performance of the algorithm and real time application is still possible.

4.5.4 An Urban Scenario

In this Scenario, an urban traffic scenario has been designed in SUMO to evaluate and test the proposed approach as shown in Figure 4.31. The parameters for this scenario are the same as the highway scenario (with the exception of the dimension

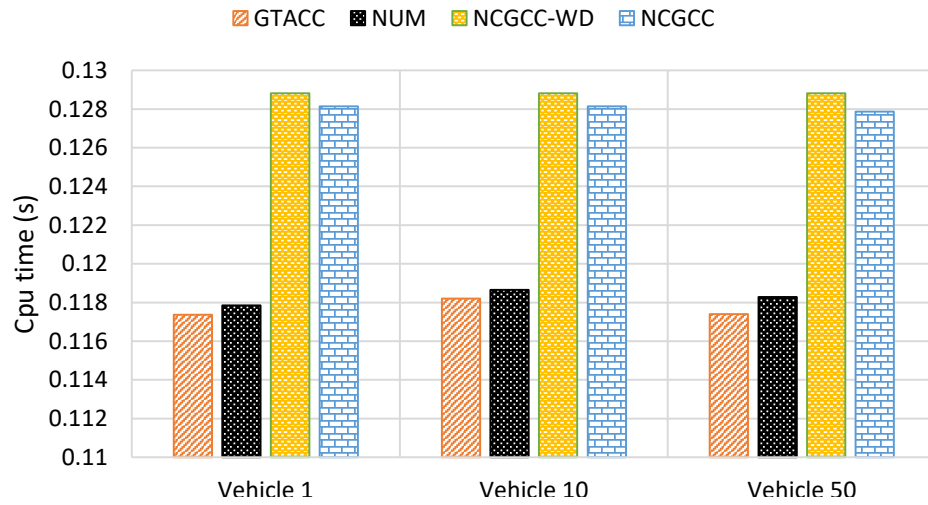


Figure 4.30: CPU time in the highway scenario

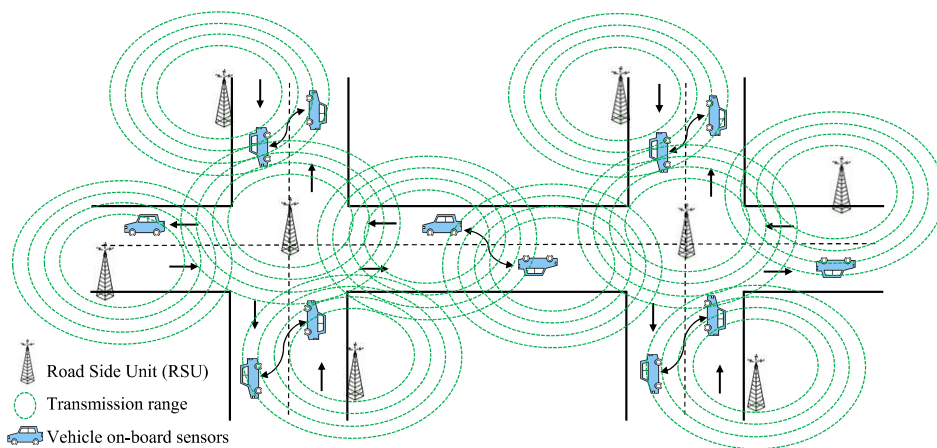


Figure 4.31: An urban scenario considered in SUMO

of the problem area and speeds of the vehicles) and are summarized in Table 4.2.

Average throughput

Figure 4.32 shows the total average throughput obtained by NUM, GTACC, NORAC and NCGACC, respectively. It is clear that the NCGACC approach has significantly improved the average throughput as compared to the NUM, GTACC and NORAC. Using GTACC, NUM, NORAC and NCGACC approaches, the total average throughput for the number of vehicles equal to 150 is 46.27, 38.42,

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

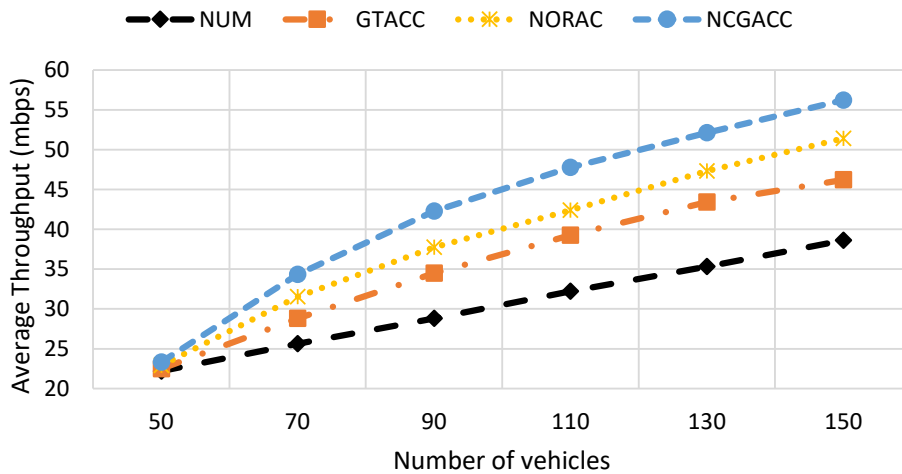


Figure 4.32: Total average throughput in the urban scenario

56.22 and 51.41 mbps in GTACC, NUM, NORAC and NCGACC, respectively. The NCGACC improves the total average throughput by an overall average of 19.29%, 40.08% and 9.7% as compared to GTACC, NUM and NORAC, respectively. The reason is that the NCGACC adapts the sending rate of vehicles based on their chosen optimal value as well as considering contention delay, message and vehicle priorities. On the other hand, both NUM GTACC and NORAC have not considered the delay in the data rate adaptation mechanism when there is congestion in the wireless channel. This leads to many messages being sent through the network at a high data rate, which in turn leads to a collision in data and congestion in wireless channel causing packet loss and thus reduced throughput.

Average delay

Figure 4.33 depicts the variation of the average delay with the number of vehicles. This is due to increasing the number of connected vehicles on the road segment increases contention among vehicles to access the wireless channel which in turn affects significantly the average delay. The results show that the delay in NCGACC strategy is significantly less than the NUM, GTACC and NORAC, respectively. Note, that there is no sharp increase in the average delay when there is an increase in the number of vehicles. This is because the NCGACC approach has a better response to the network changes and has an efficient utility function

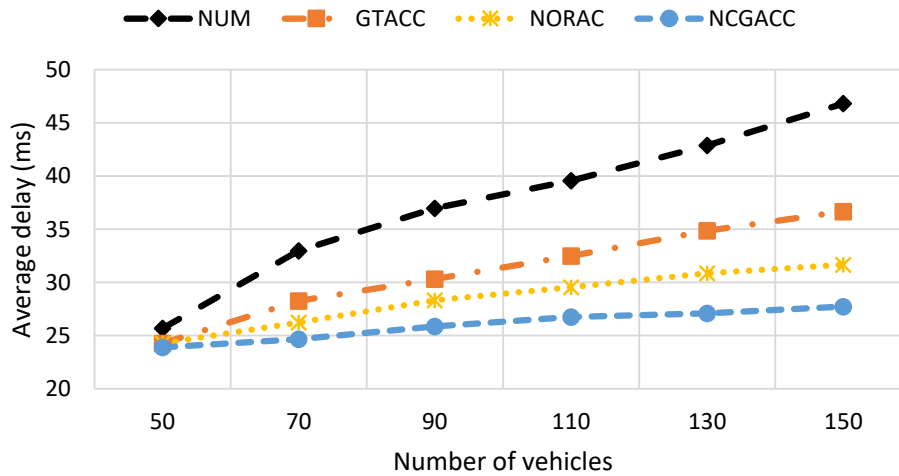


Figure 4.33: Total average delay in the urban scenario

that can successfully be used to obtain the optimal data transmission rates, which in turn minimizes the delay in receiving data packets.

Number of lost packets

Figure 4.34 illustrates the total number of lost packets in the network due to the congestion in the wireless channel. It is obvious that the number of lost packets in the NCGACC strategy is less than the NUM, GTACC and NORAC approaches. This is due to considering contention delay among vehicles when selecting an optimal data transmission rate which helps to mitigate the congestion in the wireless channel. This decreases the number of lost packets, regardless of the number of vehicles being considered.

Collision Probability

Figure 4.35 shows the collision probability variations with the number of vehicles. It is clear that the NCGACC does not give as significant an increase in the collision probability as compared to the comparison approaches. This is due to considering the contention delay parameter as an extra term in the utility function optimization. Additionally, the Figure 4.35 shows that for a number of vehicles equal to 150, the collision probabilities resulted from NCGACC approach are 3.12

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

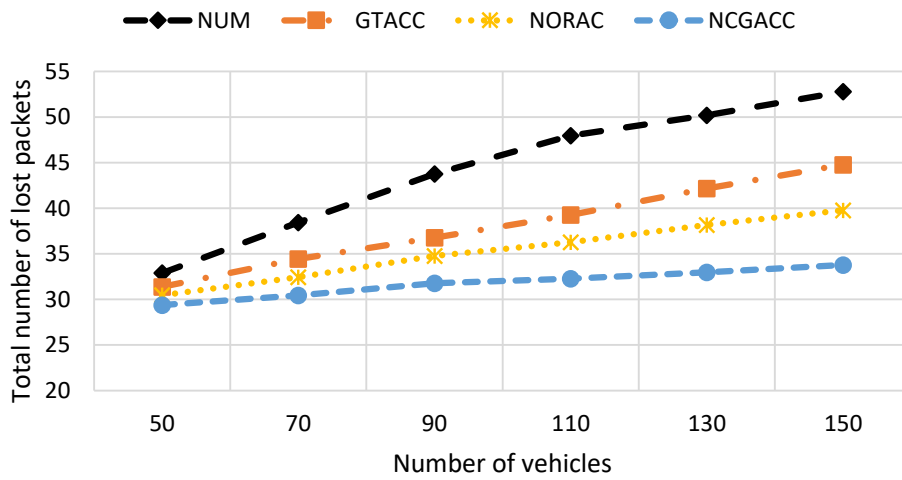


Figure 4.34: Total number of lost packets in the urban scenario

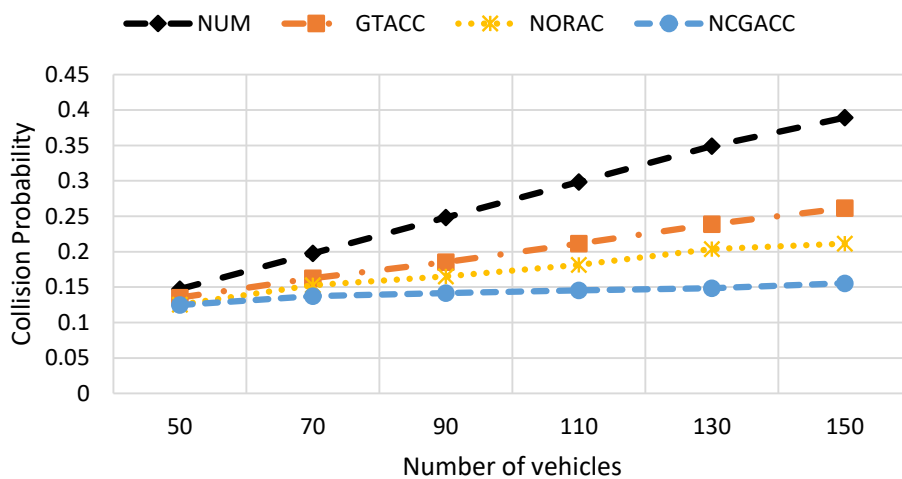


Figure 4.35: Collision probability in the urban scenario

and 1.77 times less than the collision probability obtained from NUM, GTACC and NORAC, respectively.

Packet Delivery Ratio

Figure 4.36 shows how the PDR varies with the number of vehicles in the urban scenario. It is clear from the figure that the PDR decreases by increasing the number of vehicles. However, the NCGACC has a much better PDR when compared to NUM, GTACC and NORAC approaches. These results mean that the NC-

4.5 Performance Evaluation of NCGACC

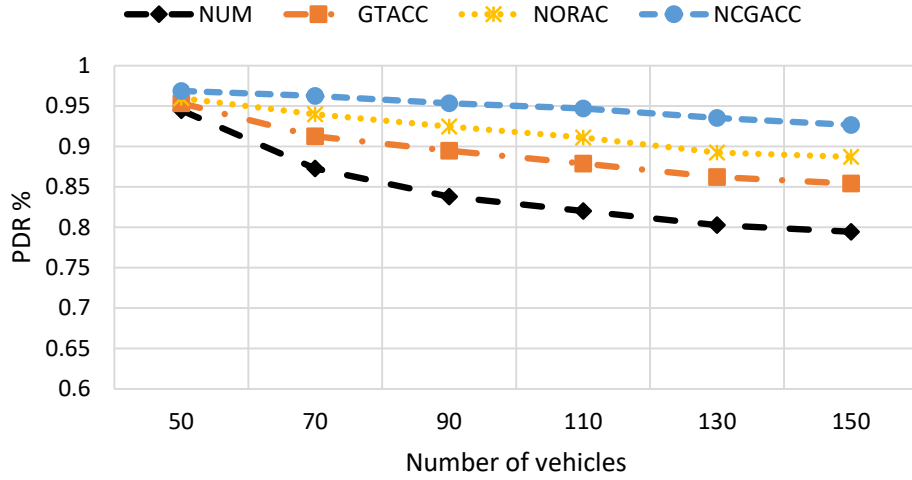


Figure 4.36: Packet delivery ratio in the urban scenario

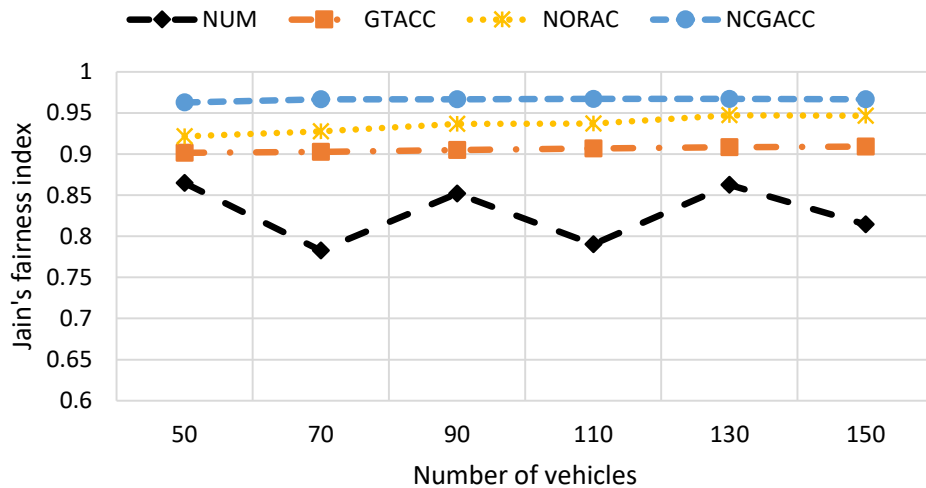


Figure 4.37: Jain's fairness index in the urban scenario

GACC decreases the number of lost packets when compared NUM, GTACC and NORAC, respectively. This is due to improving of the average throughput, average delay, collision probability via the improved mechanism for avoiding wireless channel congestion.

Jain's Fairness Index (JFI)

Figure 4.37 shows the JFI for the urban environment example. Here, it can be seen that the NCGACC approach again provides the fairest allocation of system resources. This is similar to what was shown in the previous highway scenario.

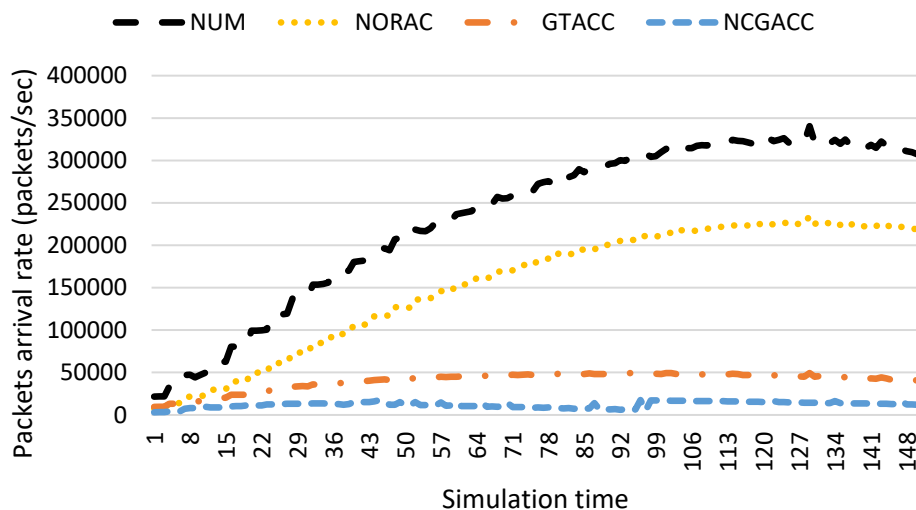


Figure 4.38: Packets Arrival Rate

Packets Arrival Rate (Packets/Sec)

Figure 4.38 shows the variation of the average arrival rate of messages with simulation time. It is clear from the Figure 4.38 that the the arrival rate increases when the vehicles send data at a high rate. However, this comes at the expense of consuming the bandwidth and increasing the load on the channel capacity. It is obvious that both GTACC and NCGACC have lower arrival rate comparing with NUM and NORIC, respectively. This is due to the adaptation mechanism of data rate in GTACC and NCGACC which allows vehicles to reduce their transmission rate in order to alleviate the channel congestion and reduce the communication overhead without a significant effect on the traffic information accuracy.

4.6 Conclusions

As the number of connected vehicles on a road network increase so does the number of transmitted messages which leads to congestion in the wireless communication channel. This degrades the network performance and the QoS parameters. In this chapter, congestion control in the communication channel has been formulated as a non-cooperative game. Each vehicle acts as a player in the game and requests a high data rate in a selfish way. Simulation results show that the GTACC has a better performance as compared to the Carrier-Sense Multiple

Access with Collision Avoidance mechanism of the Wireless Access for Vehicular Environment protocol. As reported from the highway street scenario, it is shown that the proposed approach improves the QoS parameters such as throughput, average delay, number of lost packets and total channel busy time by an overall average of 50.40%, 49.37%, 58.39% and 36.66% respectively, as compared to Carrier-Sense Multiple Access with Collision Avoidance mechanism.

This chapter also proposes another utility function that has been formulated based on the sending rate, contention delay and priorities of vehicles in VANETs. Then, the existence of a unique Nash equilibrium is derived and the solution of the optimal game is presented by using the Newton-Raphson method. Simulation results show that the NCGACC has a better performance as compared to GTACC, NUM and NORAC strategies, respectively. As reported from the highway street scenario, it is shown that the proposed approach improves the Quality of Service parameters such as throughput, average delay, number of lost packets and collision probability by an overall average of 23.51%, 57.80%, 36.32% and 35.55%, respectively as compared to GTACC, NUM and NORAC strategies.

4. A GAME THEORY APPROACH FOR CONGESTION CONTROL IN VEHICULAR AD HOC NETWORKS

Chapter 5

Filtering and Predication of Traffic Flow

5.1 Introduction

This chapter presents and evaluates traffic congestion problem using Macroscopic model. The vehicle traffic congestion occurs due to many reasons such as road limited capacity, peak hour, unplanned signalling and bottlenecks, traffic accidents, weather situations and human behaviour. In this chapter we look at the problem of estimating traffic states within segments of road using a particle filter and traffic measurements at the segment boundaries. When measurements are not available at all of the boundaries the estimation accuracy can decrease. We propose solving this problem by estimating the missing measurements by assuming the current measurements will approach the mean of historical measurements from a suitable time period. The proposed solutions come in the form of an l_1 norm minimisation and a relevance vector machine type optimisation. Test scenarios involving simulated and real data verify that an accurate estimate of the traffic measurements can be achieved and help to improve traffic state estimation accuracy of the particle filter without a significant increase in computation time. For the real data used this can be up to a 23.44% improvement in RMSE values.

The rest of this chapter is structured in the following manner. Firstly, the traffic flow model is introduced in Section 5.2. Then Section 5.3 introduces the methods of estimating the missing measurements. Section 5.4 gives details of the PF used for traffic state estimation. Then a performance evaluation is provided in Section 5.5. Finally, conclusions are drawn in Section 5.6.

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

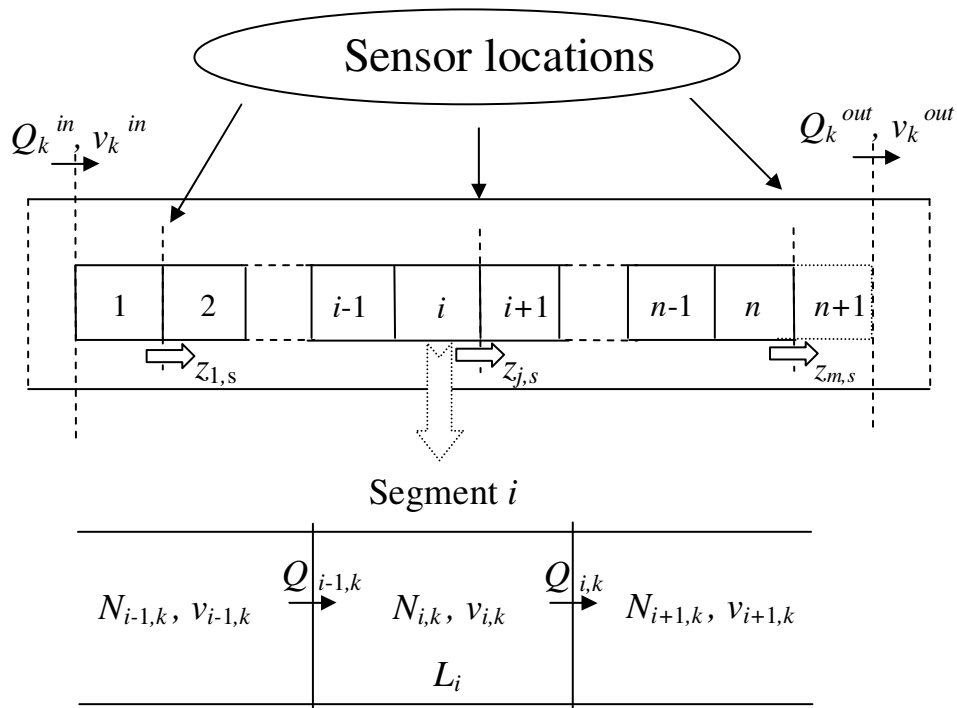


Figure 5.1: Road segments and measurements points [21]. $Q_{i,k}$ is the number of vehicles crossing the boundary between segments i and $i + 1$ at time k , $N_{i,k}$ and $v_{i,k}$ the number of vehicles and average of the vehicles, respectively.

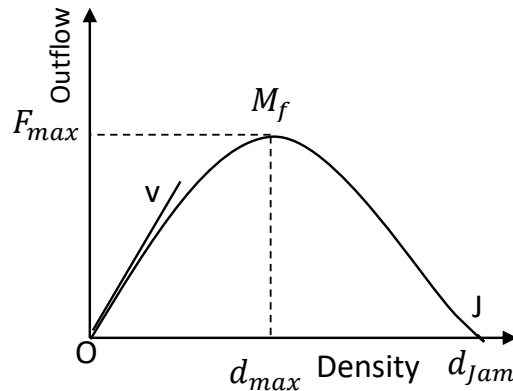


Figure 5.2: MFD flow-density relationship

5.2 Traffic Flow Models

5.2.1 A Stochastic Traffic Model

In this chapter the SCM [20] has been used, where the road is divided into segments as shown in Figure 5.1 and L_i is the length of road segment i , where segment i consists of l_i lanes. This work is interested in estimates of the traffic states at times $t_1, t_2, \dots, t_k, \dots$. The state vector is given by $\mathbf{x}_k = [\mathbf{x}_{1,k}^T, \mathbf{x}_{2,k}^T, \dots, \mathbf{x}_{n,k}^T]^T$, $\mathbf{x}_{i,k} = [N_{i,k}, v_{i,k}]^T$, where $N_{i,k}$ and $v_{i,k}$ are the number of vehicles and their average speed, respectively and $n + 1$ is the fictitious last road segment. Finally, this work assumes vehicles have an average length of A_l . The SCM is described by the Model Fundamental Diagram that joins together the traffic parameters such as speed, flow and density. Figure (5.2) shows the MFD where O represents the zero density and zero flow state. Point J denotes the zero flow and jam represents the jam density. M_f indicates the maximum flow which is corresponding to the density d_{max} . The slope of the tangent line Ov gives the average free flow speed S_f . The slope of the line (M_fJ) corresponding to the backward congestion wave propagation speed. Figure (5.3) shows the relationship between speed and density.

The evolution of the traffic states can be described by using the following

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

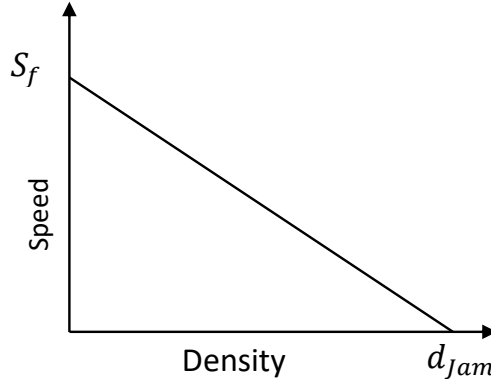


Figure 5.3: MFD speed-density relationship

equations:

$$\mathbf{x}_{1,k+1} = f_1(Q_k^{in}, v_k^{in}, \mathbf{x}_{1,k}, \mathbf{x}_{2,k}, \boldsymbol{\eta}_{1,k}), \quad (5.1)$$

$$\mathbf{x}_{i,k+1} = f_i(\mathbf{x}_{i-1,k}, \mathbf{x}_{i,k}, \mathbf{x}_{i+1,k}, \boldsymbol{\eta}_{i,k}), \quad (5.2)$$

$$\mathbf{x}_{n,k+1} = f_n(\mathbf{x}_{n-1,k}, \mathbf{x}_{n,k}, Q_k^{out}, v_k^{out}, \boldsymbol{\eta}_{n,k}), \quad (5.3)$$

where f_i is specified by the traffic model and $\boldsymbol{\eta}_k$ allows for random fluctuations and modelling error. In equations (5.1)-(5.3) Q_k^{in} and Q_k^{out} , are the vehicles entering the first segment and leaving the last segment within the time interval $\Delta t_k = t_{k+1} - t_k$ with average speeds v_k^{in} and v_k^{out} , respectively. Note, these are the boundary conditions and not traffic states to be estimated. The traffic behaviour is modelled with forward and backward propagation of traffic perturbations. This model is summarised in Algorithm 3 and the interested reader can find further details in [20]. Note, in Algorithm 3 $S_{i,k}$ and $R_{i,k}$ are the sending and receiving functions, respectively. The sending functions determine the number of vehicles that can leave a road segment, while the receiving function determines the number that can enter. Finally, $\rho_{i,k+1}^{antic}$ is an anticipated traffic density as a result of mixing densities from two neighbouring cells, ρ_{th} is a threshold value for the road traffic density and $v_{i,k+1}^{interm}$ is an intermediate traffic velocity (intermediate since it can be seen as kind of mixing velocities from neighboring cells).

Algorithm 3 The Traffic Model [21]

 1: *Forward wave:*

 For $i = 1, 2, \dots, n$

$$S_{i,k} = \max \left(N_{i,k} \frac{v_{i,k} \cdot \Delta t_k}{L_i} + \eta_{S_{i,k}}, N_{i,k} \frac{v_{min} \cdot \Delta t_k}{L_i} \right)$$

 and set $Q_{i,k} = S_{i,k}$.

End For

 2: *Backward wave:*

 For $i = n, n-1, \dots, 1$

$$R_{i,k} = N_{i+1,k}^{max} - N_{i+1,k} + Q_{i+1,k},$$

where

$$N_{i+1,k}^{max} = (L_{i+1} \ell_{i+1,k}) / (A_\ell + v_{i+1,k} t_d),$$

 if $S_{i,k} < R_{i,k}$, $Q_{i,k} = S_{i,k}$ else $Q_{i,k} = R_{i,k}$,

$$v_{i,k} = Q_{i,k} L_i / (N_{i,k} \Delta t_k).$$

End For

3: Update the number of vehicles inside segments:

 For $i = 1, 2, \dots, n$

$$N_{i,k+1} = N_{i,k} + Q_{i-1,k} - Q_{i,k}.$$

End For

4: Update the density:

 For $i = 1, 2, \dots, n$

$$\rho_{i,k+1} = N_{i,k+1} / (L_i \ell_{i,k+1}),$$

$$\rho_{i,k+1}^{antic} = \alpha \rho_{i,k+1} + (1 - \alpha) \rho_{i+1,k+1}.$$

End For

5: Update of the speed:

 For $i = 1, 2, \dots, n$

$$v_{i,k+1}^{interm} = \begin{cases} \frac{v_{i-1,k} Q_{i-1,k} + v_{i,k} (N_{i,k} - Q_{i,k})}{N_{i,k+1}}, & N_{i,k+1} \neq 0, \\ v_f, & \text{otherwise,} \end{cases}$$

$$v_{i,k+1}^{interm} = \max(v_{i,k+1}^{interm}, v_{min})$$

$$v_{i,k+1} = \beta_{k+1} v_{i,k+1}^{interm} + (1 - \beta_{k+1}) v^e(\rho_{i,k+1}^{antic}) + \eta_{v_{i,k+1}},$$

$$\beta_{k+1} = \begin{cases} \beta^I, & |\rho_{i+1,k+1}^{antic} - \rho_{i,k+1}^{antic}| \geq \rho_{th}, \\ \beta^{II} & \text{otherwise.} \end{cases}$$

 End For

5.2.2 The Measurements Model

There are then sensors, e.g. magnetic loops, radar or video cameras, on the boundaries of various road segments. measurements of the number of vehicles crossing the segment boundaries and their speeds are made at the discrete time points of interest, given by t_s . The result of this is the measurements vector given by $\mathbf{z}_s = [\mathbf{z}_{1,s}^T, \mathbf{z}_{2,s}^T, \dots, \mathbf{z}_{m,s}^T]^T$ where there are measurements made at m boundaries and $\mathbf{z}_{j,s} = [\bar{Q}_{j,s}, \bar{v}_{j,s}]^T$.

Given the measurements equation

$$\mathbf{z}_s = h(\mathbf{x}_s, \boldsymbol{\xi}_s), \quad (5.4)$$

where $h(\cdot)$ is determined by the measurements model used. If we know the distribution of the initial state vector then the traffic state estimation problem becomes a recursive Bayesian estimation problem and can be solved with a PF (see Section 5.4). In this work we assume $\boldsymbol{\xi}_s = [\xi_{Q_{j,s}}, \xi_{v_{j,s}}]^T$ is a Gaussian measurements noise giving:

$$\mathbf{z}_{j,s} = \begin{pmatrix} \bar{Q}_{j,s} \\ \bar{v}_{j,s} \end{pmatrix} + \boldsymbol{\xi}_s. \quad (5.5)$$

5.3 Dealing with the Missing Measurements

5.3.1 Compressive Sensing

At a given time t_s , the actual measurements are given by $\mathbf{z}_s = [\mathbf{z}_{1,s}^T, \mathbf{z}_{2,s}^T, \dots, \mathbf{z}_{n,s}^T]^T$, where n is the number of road segment boundaries. However, not all of these measurements will be available at time t_s . Instead we can estimate these missing measurements. Firstly, consider a measurements matrix given by

$$\mathbf{m}_s = \mathbf{b}_s \circ \mathbf{z}_s, \quad (5.6)$$

where \circ is the Hadamard product,

$$\mathbf{b}_s = [b_{s,1}, b_{s,2}, \dots, b_{s,2n}]^T \quad (5.7)$$

5.3 Dealing with the Missing Measurements

and

$$b_{s,i} = \begin{cases} 1, & \text{measurements available,} \\ 0 & \text{measurements unavailable.} \end{cases} \quad (5.8)$$

This measurements matrix can now be used to gain an estimate of the current measurements $\hat{\mathbf{z}}_s$.

We assume that the current measurements at the segment boundaries will be close to the mean of the historical measurements (or corresponding estimates) over a suitable period of time, defined by the length t_h . This is given by

$$\tilde{\mathbf{z}}_s = \tilde{\phi}_s \tilde{\theta}_s, \quad (5.9)$$

where $\tilde{\theta}_s = [1/t_h, 1/t_h, \dots, 1/t_h]^T$ ($\tilde{\theta}_s \in \mathbb{R}^{t_h \times 1}$) and $\tilde{\phi}_s$ is the relevant historical measurements/estimates, given by

$$\tilde{\phi}_s = [\phi_{s-t_h}, \phi_{s-t_h+1}, \dots, \phi_s] \quad (5.10)$$

and

$$\phi_j = [\phi_{1,j}^T, \phi_{2,j}^T, \dots, \phi_{n,j}^T]^T, \quad (5.11)$$

$$\phi_{i,j} = \begin{cases} \mathbf{z}_{i,j}, & \text{measurements available,} \\ \hat{\mathbf{z}}_{i,j} & \text{measurements unavailable.} \end{cases} \quad (5.12)$$

This gives us the following problem

$$\min \|\tilde{\mathbf{z}}_s - \hat{\mathbf{z}}_s\|_1, \quad (5.13)$$

where $\|\cdot\|_1$ is the l_1 norm. Minimising the l_0 norm would give the smallest amount of non-zero values for $\tilde{\mathbf{z}}_s - \hat{\mathbf{z}}_s$. However, this can not be achieved in practice and the l_1 norm is used as an approximation [34,35]. Note, $\|\tilde{\mathbf{z}}_s - \hat{\mathbf{z}}_s\|_1$ can be written as follows

$$\begin{aligned} \|\tilde{\mathbf{z}}_s - \hat{\mathbf{z}}_s\|_1 &= \|\tilde{\phi}_s \tilde{\theta}_s - \tilde{\phi}_s \hat{\theta}_s\|_1 \\ &= \|\tilde{\phi}_s (\tilde{\theta}_s - \hat{\theta}_s)\|_1 = |\tilde{\phi}_s| \|\tilde{\theta}_s - \hat{\theta}_s\|_1. \end{aligned} \quad (5.14)$$

Therefore, as $|\tilde{\phi}_s|$ is constant at a given time the minimisation in (5.13) can be achieved by $\min_{\hat{\theta}_s} \|\tilde{\theta}_s - \hat{\theta}_s\|_1$.

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

However, this will always aim to have $\tilde{\boldsymbol{\theta}}_s = \hat{\boldsymbol{\theta}}_s$. As a result a constraint has to be added to ensure that the estimated measurements do not disagree with the available measurements matrix. In other words we want to place a limit on $\|\mathbf{m}_s - \mathbf{b}_s \circ \hat{\mathbf{z}}_s\|_2 = \|\mathbf{m}_s - (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)\hat{\boldsymbol{\theta}}_s\|_2$, where $\mathbf{B} = [\mathbf{b}_s, \mathbf{b}_s, \dots, \mathbf{b}_s]$ ($\mathbf{B} \in \mathbb{R}^{t_h \times 1}$). This results in:

$$\min_{\hat{\boldsymbol{\theta}}_s} \|\tilde{\boldsymbol{\theta}}_s - \hat{\boldsymbol{\theta}}_s\|_1 \quad \text{subject to} \quad \|\mathbf{m}_s - (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)\hat{\boldsymbol{\theta}}_s\|_2 \leq \varepsilon. \quad (5.15)$$

Here the constant ε in the added constraint places a limit on the error between the available measurements vector and the corresponding estimated measurements. The final estimate is then given by

$$\hat{\mathbf{z}}_{s,CS} = \tilde{\boldsymbol{\phi}}_s \hat{\boldsymbol{\theta}}_s. \quad (5.16)$$

5.3.2 Bayesian Compressive Sensing

The relevance vector machine (RVM) is a Bayesian approach which does not experience from any of the Support Vector Machine (SVM) weaknesses such as make unnecessarily free use of basis functions since the number of support vectors required typically grows linearly with the size of the training set. Especially, we utilise a fully probabilistic model and assume a prior over the model weights supervised by a set of hyperparameters, one correlated with each weight, whose most feasible values are iteratively determined from the data. Sparsity is obtained because in practice we obtain that the posterior distributions of many of the weights are clearly (indeed infinitely) peaked around zero. We term those training vectors connected with the remaining non-zero weights ‘relevance’ vectors. The most compelling characteristic of the RVM is that, while able of generalization performance comparable to an equivalent SVM, it typically utilizes dramatically fewer kernel functions [40]. Therefore, in this thesis the problem of the missing measurements can be formulated in a Bayesian framework. Firstly, we know

$$\mathbf{m}_s = (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)\hat{\boldsymbol{\theta}}_s + \mathbf{e}_s, \quad (5.17)$$

5.3 Dealing with the Missing Measurements

where we assume \mathbf{e}_s to be Gaussian noise with a variance σ^2 . The solution is then found by evaluating

$$\hat{\boldsymbol{\theta}}_{s,BCS} = \max \mathcal{P}(\hat{\boldsymbol{\theta}}_s, \sigma^2, \mathbf{p}_s | \mathbf{m}_s, \tilde{\boldsymbol{\theta}}_s), \quad (5.18)$$

where $\mathbf{p}_s = [p_{s,1}, p_{s,2}, \dots, p_{s,2n}]^T$ are hyper-parameters to be estimated.

As per (5.17) the likelihood is given by

$$\mathcal{P}(\mathbf{m}_s | \hat{\boldsymbol{\theta}}_s, \sigma^2) = (2\pi\sigma^2)^{-n} \exp \left\{ -\frac{1}{2\sigma^2} \|\mathbf{m}_s - (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s) \hat{\boldsymbol{\theta}}_s\|_2^2 \right\}. \quad (5.19)$$

We further assume that the values of $\hat{\boldsymbol{\theta}}_s$ will be likely to be close to those of $\tilde{\boldsymbol{\theta}}_s$, which gives us the prior distribution

$$\begin{aligned} \mathcal{P}(\hat{\boldsymbol{\theta}}_s | \mathbf{p}_s, \tilde{\boldsymbol{\theta}}_s) &= (2\pi)^{-tn/2} |\mathbf{P}_s|^{1/2} \\ &\times \exp \left\{ -\frac{1}{2} (\hat{\boldsymbol{\theta}}_s - \tilde{\boldsymbol{\theta}}_s) \mathbf{P}_s (\hat{\boldsymbol{\theta}}_s - \tilde{\boldsymbol{\theta}}_s)^T \right\}. \end{aligned} \quad (5.20)$$

Here, $|\mathbf{P}_s|$ is the of determinant $\mathbf{P}_s = \text{diag}(\mathbf{p}_s)$.

In order to avoid the over-fitting problem, the parameters are constrained by defining an explicit prior over them.

$$\mathcal{P}(\mathbf{w} | \mathbf{p}_s) = \prod_{i=1}^{2n} \mathcal{N}(w_i | 0, p_s^{-1}). \quad (5.21)$$

With \mathbf{p}_s being a vector of $(N+1)$ hyperparameters. To complete the specification of this hierarchical prior, now we must place independent Gamma priors on the hyperparameters $p_s; i$ giving

$$\mathcal{P}(\mathbf{p}_s) = \prod_{i=1}^{2n} G(p_{s,i} | a, b). \quad (5.22)$$

A further Gamma prior can also be used for σ^2

$$\mathcal{P}(\sigma^2) = G(\sigma^{-2} | c, d), \quad (5.23)$$

where a, b, c and d are scale and shape priors. With these definitions we can now find the solution to (5.18) by following a RVM type framework [40]. We know

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

that

$$\mathcal{P}(\hat{\boldsymbol{\theta}}_s, \sigma^2, \mathbf{p}_s | \mathbf{m}_s, \tilde{\boldsymbol{\theta}}_s) = \mathcal{P}(\hat{\boldsymbol{\theta}}_s | \mathbf{m}_s, \sigma^2, \mathbf{p}_s, \tilde{\boldsymbol{\theta}}_s) \mathcal{P}(\mathbf{p}_s, \sigma^2 | \mathbf{m}_s) \quad (5.24)$$

and

$$\begin{aligned} \mathcal{P}(\hat{\boldsymbol{\theta}}_s | \mathbf{m}_s, \sigma^2, \mathbf{p}_s, \tilde{\boldsymbol{\theta}}_s) &= \frac{\mathcal{P}_s(\mathbf{m}_s | \hat{\boldsymbol{\theta}}_s, \sigma^2) \mathcal{P}(\hat{\boldsymbol{\theta}}_s | \mathbf{p}_s, \hat{\boldsymbol{\theta}}_s)}{\mathcal{P}(\mathbf{m}_s | \mathbf{p}_s, \sigma^2, \tilde{\boldsymbol{\theta}}_s)} \\ &= (2\pi)^{-t_h/2} |\boldsymbol{\Sigma}_s|^{-1/2} \exp \left\{ -\frac{1}{2} \right. \\ &\quad \left. \times (\hat{\boldsymbol{\theta}}_s - \boldsymbol{\mu}_s)^T \boldsymbol{\Sigma}_s^{-1} (\hat{\boldsymbol{\theta}}_s - \boldsymbol{\mu}_s) \right\}, \end{aligned} \quad (5.25)$$

where $\boldsymbol{\Sigma}_s$ and $\boldsymbol{\mu}_s$ are the covariance matrix and mean vector given by

$$\boldsymbol{\Sigma}_s = (\sigma^{-2} (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)^T (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s) + \mathbf{P}_s)^{-1}, \quad (5.26)$$

and

$$\boldsymbol{\mu}_s = \boldsymbol{\Sigma}_s (\sigma^{-2} (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)^T \mathbf{m}_s + \mathbf{P}_s \tilde{\boldsymbol{\theta}}_s), \quad (5.27)$$

respectively.

Following a similar method to [40] we have

$$\mathcal{P}(\sigma^2, \mathbf{p}_s | \mathbf{m}_s) \approx \mathcal{P}(\mathbf{m}_s | \mathbf{p}_s, \sigma^2, \tilde{\boldsymbol{\theta}}_s) \mathcal{P}(\mathbf{p}_s) \mathcal{P}(\sigma^2), \quad (5.28)$$

where if we have $a = b = c = d = 10^{-4}$ then $\mathcal{P}(\mathbf{p}_s)$ and $\mathcal{P}(\sigma^2)$ are non-informative [40]. These are shape and scale parameters that control the distribution. The selection of these parameters is standard for the method applied. According to [40], they have to be greater than zero by definition and by having them small the distributions become non-informative which expresses vague or general information about a variable. Relevance vector machine becomes the search of the hyperparameters that maximize 5.28 with respect to \mathbf{p}_s and σ^2 . A large values of $p_{s,i}$ are led to large values (in principle they become infinite) during the learning procedure. Thus, $\mathcal{P}(\hat{\boldsymbol{\theta}}_s | \mathbf{m}_s, \sigma^2, \mathbf{p}_s, \tilde{\boldsymbol{\theta}}_s)$ becomes highly peaked around zero. We are a posteriori or certain that these $\hat{\boldsymbol{\theta}}_s$ are zero and sparsity is realized. Therefore, the vectors $(\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)$ for which $\hat{\boldsymbol{\theta}}_s$ are not zero are called relevance vectors.

5.3 Dealing with the Missing Measurements

As a result, maximising $\mathcal{P}(\sigma^2, \mathbf{p}_s | \mathbf{M}_s)$ is equivalent to maximising $\mathcal{P}(\mathbf{m}_s | \mathbf{p}_s, \sigma^2, \tilde{\boldsymbol{\theta}}_s)$. This can be achieved by maximising

$$\begin{aligned}
\mathcal{L}(\mathbf{p}_s, \sigma^2) &= \log \left\{ (2\pi\sigma^2)^{-t_h/2} |\boldsymbol{\Sigma}_s|^{\frac{1}{2}} |\mathbf{P}_s|^{\frac{1}{2}} \exp \left(-\frac{1}{2} \right. \right. \\
&\quad \times \left. \left. (\mathbf{m}_s^T \mathbf{C} \mathbf{m}_s + \tilde{\boldsymbol{\theta}}_s^T \mathbf{D}_s \tilde{\boldsymbol{\theta}}_s \right. \right. \\
&\quad \left. \left. - 2\sigma^2 \mathbf{m}_s^T (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s) \boldsymbol{\Sigma}_s \mathbf{P}_s \tilde{\boldsymbol{\theta}}_s) \right) \right\} \\
&= -\frac{1}{2} \left(t_h \log(2\pi) + t_h \log \sigma^2 - \log |\boldsymbol{\Sigma}_s| - \right. \\
&\quad \left. \log |\mathbf{P}_s| + \sigma^{-2} \|\mathbf{m}_s - (\mathbf{B}_s \circ \boldsymbol{\phi}_s) \boldsymbol{\mu}_s\|_2^2 \right. \\
&\quad \left. + \boldsymbol{\mu}_s^T \mathbf{P} \boldsymbol{\mu}_s + \tilde{\boldsymbol{\theta}}_s^T \mathbf{P}_s \tilde{\boldsymbol{\theta}}_s - \tilde{\boldsymbol{\theta}}_s^T \mathbf{P}_s \boldsymbol{\mu}_s \right), \tag{5.29}
\end{aligned}$$

where $\mathbf{C}_s = (\sigma^2 \mathbf{I} + (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}) \mathbf{P}_s^{-1} (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}})^T)^{-1}$ and $\mathbf{D}_s = \mathbf{P}_s - \mathbf{P}_s^T \boldsymbol{\Sigma}_s \mathbf{P}_s$.

By differentiating (5.29) with respect to $p_{s,i}$ and σ^{-2} it possible to get the update equations for the precision hyperparameters and variance, respectively. This gives us

$$p_{s,i}^{new} = \frac{\gamma_{s,i}}{\mu_{s,i}^2 + \tilde{\boldsymbol{\theta}}_{s,i} - \tilde{\boldsymbol{\theta}}_{s,i} \mu_{s,i}}, \tag{5.30}$$

$$\sigma_{new}^2 = \frac{\|\mathbf{m}_s - (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s) \boldsymbol{\mu}_s\|_2^2}{t_h - \sum_i \gamma_{s,i}}, \tag{5.31}$$

where $\gamma_{s,i} = 1 - p_{s,i} \Sigma_{s,ii}$, $\Sigma_{s,ii}$ is the i^{th} diagonal element of $\boldsymbol{\Sigma}_s$.

The optimisation is then achieved by iteratively finding $\boldsymbol{\Sigma}_s$ and $\boldsymbol{\mu}_s$, followed by $p_{s,i}^{new}$ and σ_{new}^2 until a convergence criterion is met. To obtain the final estimates of $\hat{\boldsymbol{\theta}}_s$ the optimised values of \mathbf{p}_s and σ^2 are put into (5.27) to give

$$\begin{aligned}
\hat{\mathbf{z}}_{s,BCS} &= \left(\frac{(\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)^T (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)}{\sigma_{opt}^2} + \mathbf{P}_{s,opt} \right)^{-1} \\
&\quad \times \left(\frac{(\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)^T \mathbf{m}_s}{\sigma_{opt}^2} + \mathbf{P}_{s,opt} \tilde{\boldsymbol{\theta}}_s \right). \tag{5.32}
\end{aligned}$$

The primary idea is that (6.29) and (6.30) are evaluated with the current means and covariances. These new values are used to find new mean and covariance and so on. It is a similar idea to the Expectation-Maximization (EM) algorithm. EM

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

is used as an approach in order to calculate iteratively the maximum likelihood of variables in statistical models. EM has two steps to execute the iteration that are the Expectation (E) and maximization (M) steps. E step uses the current state of the model or system to represent the expectation of estimated log-likelihood with a function. In the M step, the parameters that maximize the observed log-likelihood expectation on the E step are calculated. These calculated parameters are then used to determine the hidden parameters distribution in the following E step.

Either the estimates $\hat{\mathbf{z}}_{s,CS}$ or $\hat{\mathbf{z}}_{s,BCS}$ can then be used to replace the available measurements used with in a PF. Such a scheme is detailed in the next section.

5.4 Particle Filtering Framework for Traffic State Estimation

5.4.1 The Particle Filter Approach

The Kalman filter has been used in order to find a solution to the state space models. However, The Kalman filter estimation can only be employed to find the optimal solution for linear Gaussian problems. The extended Kalman filter and the unscented Kalman filter can be applied in order to find the optimal solution of non-linear non-Gaussian conditions. However, they fail to produce a feasible prediction when the systems are highly nonlinear and non-Gaussian.

Particle filtering methods provide an alternative approach. They are considered as one of the most powerful numerical methods that have been utilized in order to find the solution of optimal predicting problems in non-linear situations. They are running online to approximate the posterior density function of the potential operation as observations become possible. An importance sampling method is applied at each time point to approximate the distribution with a set of random samples, known as particles, associated with weights and to compute estimates based on these samples and weights.

Particle filtering aims to find the posterior probability density function of the state space model \mathbf{x}_k at time t_k given a set of observation up to the same point in time. In other words, It requires to estimate $p(\mathbf{x}_t|\mathbf{Z}^t)$, where the \mathbf{x}_k is given as

5.4 Particle Filtering Framework for Traffic State Estimation

follows:

$$\mathbf{x}_k = \mathbf{f}_{k-1}(\mathbf{x}_{k-1}, \boldsymbol{\eta}_{k-1}), \quad (5.33)$$

where \mathbf{f}_{k-1} represents known non-linear function and $\boldsymbol{\eta}_{k-1}$ denotes the random fluctuations and modelling error.

The measurements model $\hat{\mathbf{Z}}^k = [\hat{\mathbf{z}}_1, \dots, \hat{\mathbf{z}}_k]$ and $\hat{\mathbf{z}}_i$ for $i = 1, \dots, k$ is given as follows:

$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k, \boldsymbol{\xi}_k), \quad (5.34)$$

where $\mathbf{h}(\cdot)$ is determined by the measurement model used. The \mathbf{x}_t and $\boldsymbol{\xi}_t$ represent the state space model and a measurement noise, receptively. From Bayes rule

Here the aim is to find the posterior probability density function (PDF) of the state at time t_k given a set of measurements up to the same point in time. In other words we want to evaluate $p(\mathbf{x}_k | \hat{\mathbf{Z}}^k)$, where $\hat{\mathbf{Z}}^k = [\hat{\mathbf{z}}_1, \dots, \hat{\mathbf{z}}_k]$ and $\hat{\mathbf{z}}_i$ for $i = 1, \dots, k$ is estimated using (5.16) or (5.32). From Bayes rule

$$p(\mathbf{x}_k | \hat{\mathbf{Z}}^k) = \frac{p(\hat{\mathbf{z}}_k | \mathbf{x}_k) p(\mathbf{x}_k | \hat{\mathbf{Z}}^{k-1})}{p(\hat{\mathbf{z}}_k | \hat{\mathbf{Z}}^{k-1})}, \quad (5.35)$$

where

$$p(\mathbf{x}_k | \hat{\mathbf{Z}}^{k-1}) = \int_{\mathbb{R}^{n_x}} p(\mathbf{x}_k | \mathbf{x}_{k-1}) p(\mathbf{x}_{k-1} | \hat{\mathbf{Z}}^{k-1}) d\mathbf{x}_{k-1} \quad (5.36)$$

and $p(\hat{\mathbf{z}}_k | \hat{\mathbf{Z}}^{k-1})$ is a normalising constant. This means $p(\mathbf{x}_k | \hat{\mathbf{Z}}^k)$ can be updated using the following proportionality relationship:

$$p(\mathbf{x}_k | \hat{\mathbf{Z}}^k) \propto p(\hat{\mathbf{z}}_k | \mathbf{x}_k) p(\mathbf{x}_k | \hat{\mathbf{Z}}^{k-1}). \quad (5.37)$$

This recursive estimation is computationally expensive which is why PFs are used to give an approximate solution [32, 33]. Algorithm 4 gives the PF (with M_{pf}) for traffic state estimation that is considered in this thesis. We refer the interested reader to [21] for further details. The difference between this work and the algorithm shown here is the inclusion of the measurements estimation step which has been detailed in the section above. Note the inclusion of $t_k \equiv t_s$ is to account for the fact that we do not necessarily have measurements available at every time step within the particle filter.

Resampling contains of drawing M_{pf} new samples/particles from posterior

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

Algorithm 4 Particle Filter with CS/BCS Estimated measurements for Traffic State Estimation [21]

- 1: Initialization: $k = 0$
 For $l = 1, \dots, M_{pf}$
 Generate samples $\{\mathbf{x}_0^{(l)}\}$ from the initial distribution
 $p(\mathbf{x}_0)$ and initial weights $w_0^{(l)} = 1/M_{pf}$.
 End For
- 2: Prediction step:
 For $l = 1, \dots, M_{pf}$,
 sample $\mathbf{x}_k^{(l)} \sim p(\mathbf{x}_k | \mathbf{x}_{k-1}^{(l)})$ according to (4)-(11) for
 segments between two boundaries where
 measurements arrive
 End For
- 3: Missing measurements estimation (only for $t_k \equiv t_s$): Obtain the estimated
 traffic measurements, using either

$$\min_{\hat{\boldsymbol{\theta}}_s} \|\tilde{\boldsymbol{\theta}}_s - \hat{\boldsymbol{\theta}}_s\|_1 \quad \text{subject to} \quad \|\mathbf{m}_s - (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s) \hat{\boldsymbol{\theta}}_s\|_2 \leq \varepsilon,$$

$$\hat{\mathbf{z}}_s = \tilde{\boldsymbol{\phi}}_s \hat{\boldsymbol{\theta}}_s.$$

or

$$\begin{aligned} \hat{\mathbf{z}}_s &= \left(\frac{(\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)^T (\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)}{\sigma_{opt}^2} + \mathbf{P}_{s,opt} \right)^{-1} \\ &\times \left(\frac{(\mathbf{B}_s \circ \tilde{\boldsymbol{\phi}}_s)^T \mathbf{m}_s}{\sigma_{opt}^2} + \mathbf{P}_{s,opt} \tilde{\boldsymbol{\theta}}_s \right). \end{aligned}$$

- 4: Estimated measurements processing step (only for $t_k \equiv t_s$) compute the
 weights:
 For $l = 1, \dots, M_{pf}$
 $w_s^{(l)} = w_{s-1}^{(l)} p(\hat{\mathbf{z}}_s | \mathbf{x}_s^{(l)})$,
 End For
 where the likelihood $p(\hat{\mathbf{z}}_s | \mathbf{x}_s^{(l)})$ is calculated by the model (5.5) from Section
 5.2.2.
 For $l = 1, \dots, M_{pf}$
 Normalize the weights: $\hat{w}_s^{(l)} = w_s^{(l)} / \sum_{l=1}^{M_{pf}} w_s^{(l)}$.
 End For
 - 5: Output: $\hat{\mathbf{x}}_s = \sum_{l=1}^{M_{pf}} \hat{w}_s^{(l)} \mathbf{x}_s^{(l)}$,
 - 6: Selection step (resampling) only for $t_k \equiv t_s$:
 Multiply/ Suppress samples $\mathbf{x}_s^{(l)}$ with high/ low importance weights $\hat{w}_s^{(l)}$, in
 order to obtain M random samples approximately distributed according to
 $p(\mathbf{x}_s^{(l)} | \hat{\mathbf{Z}}^s)$, e.g. by residual resampling.
 For $l = 1, \dots, M_{pf}$,
 $w_s^{(l)} = \hat{w}_s^{(l)} = 1/M_{pf}$,
 End For
 - 7: $k \leftarrow k + 1$ and return to step (1).
-

PDF. This process consist of eliminates samples with low weights and replicates samples with high weights that have high probability values or high opportunity to be chosen. Most probable particles have a higher weighting and are replicated/repeated. Lower weighted particles discarded. Here, in this thesis the residual resampling method has been applied in order to draw new particles from the PDF such as in [154, 155].

5.5 Performance Evaluation

In this section we will provide a performance evaluation of the proposed algorithms. This will be formed of two parts: Firstly simulated and real data will be used to test how well (5.16) and (5.32) can fill in the missing measurements at road segment boundaries. Note, (5.16) is solved using `cvx` [156, 157]. Then a PF with and without estimated measurements will be used to estimate the traffic states for the real data. All comparisons are implemented in Matlab on a computer with an Intel Xeon CPU E3-1271 (3.60GHz) and 16GB of RAM.

The simulated data comes from the SUMO traffic simulator [158]. We simulated two 1km lanes of traffic travelling in one direction with a maximum speed of 25m/s. An induction loop was placed every 0.5km to take the segment boundary measurements every 30 seconds.

Figure 5.4 shows the section of freeway considered between Ghent and Antwerp in Belgium. The labels CLOF-CLO9 refer to the traffic cameras at road segment boundaries on the section of road being considered. Theses cameras record the number of vehicles passing the boundaries in 1 minute intervals and their average speeds.

5.5.1 Evaluation of CS and BCS based measurements estimation methods

For the SUMO simulator we assume that there are measurements available at all of the loop locations for $t_h = 25$ time instances. After this we then assume that there only measurements available at the first and last loop location. For the real data we initially have measurements available at CLOE-CLOB and start at a time of 5pm. When the estimates have been found they can then replace

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

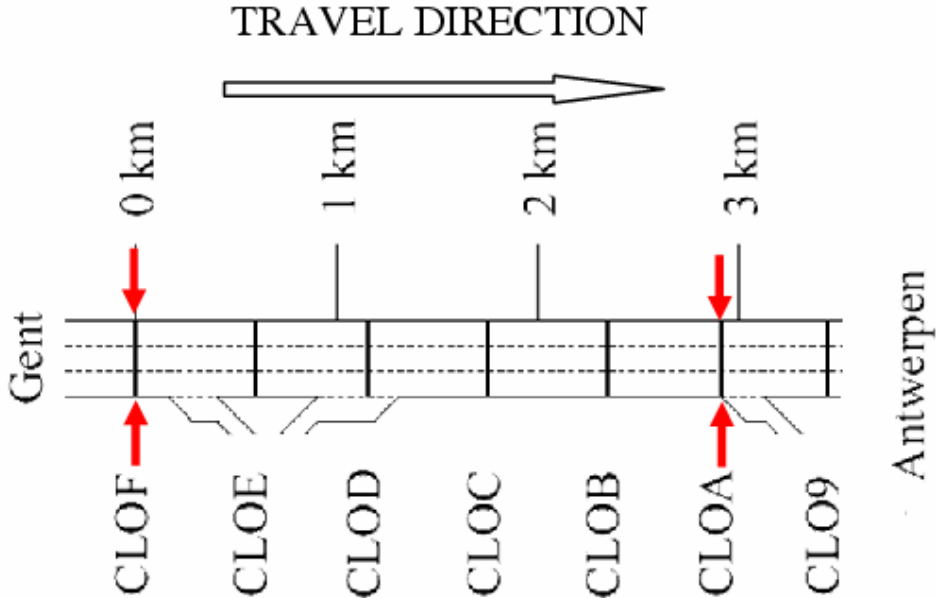


Figure 5.4: Schematic of Belgium freeway considered [21]. CLOF-CLO9 show the locations of cameras used to make the traffic measurements

the measurements at the current time instance and the process repeated for the desired length of time (20 time steps in total).

Firstly, 100 independent sets of estimates were found using (5.32) and a representative example selected. This was achieved using initial estimates of the hyperparameters as $p_{s,i} = (2n)^{-2}$, where $2n$ gives the number of measurements, and initial estimate of the variance for the Gaussian noise as $\sigma^2 = 0.1$. Then from the representative sample a value of ε for use in (5.16) can be found to allow fair comparison.

Table 5.1: Performance summary for the CS and BCS based measurements estimation methods with simulated data.

Method	CS	BCS
Computation time (s) total (per snapshot)	3.79 (0.39)	0.81 (0.04)
$\max(\ \mathbf{z}_{1,s} - \hat{\mathbf{z}}_{1,F,s}\ _2)$	6.14	5.08
$\ \mathbf{z}_{1,s} - \hat{\mathbf{z}}_{1,F,s}\ _2$	1.89	2.21
$\max(\ \mathbf{z}_{2,s} - \hat{\mathbf{z}}_{2,F,s}\ _2)$	5.16	5.15
$\ \mathbf{z}_{2,s} - \hat{\mathbf{z}}_{2,F,s}\ _2$	2.31	2.60

Table 5.2: Performance summary for the CS and BCS based measurements estimation methods with real data.

Method	CS	BCS
Computation time (s) total (per snapshot)	6.44 (0.40)	0.70 (0.03)
$\max(\ \mathbf{z}_{1,s} - \hat{\mathbf{z}}_{1,F,s}\ _2)$	9.74	8.04
$\ \mathbf{z}_{1,s} - \hat{\mathbf{z}}_{1,F,s}\ _2$	6.22	4.85
$\max(\ \mathbf{z}_{2,s} - \hat{\mathbf{z}}_{2,F,s}\ _2)$	28.56	24.43
$\ \mathbf{z}_{2,s} - \hat{\mathbf{z}}_{2,F,s}\ _2$	15.56	9.62

Table 5.1 summarises the performance of the two methods for the simulated data, where $\|\mathbf{z}_{1,s} - \hat{\mathbf{z}}_{1,F,s}\|_2$ and $\|\mathbf{z}_{2,s} - \hat{\mathbf{z}}_{2,F,s}\|_2$, for $s = t_{init}, \dots, t_{init} + t_h$ and $F = \{CS, BCS\}$, is used to indicate the estimation accuracy. Note, the subscript 1 refers to the measurements related to vehicle speed and the subscript 2 for the number of vehicles. From this we can see that both methods give a comparable performance in terms of estimation accuracy. For the CS based method this relates to the speed estimate always being within 3.66 m/s of the actual measurements and 3.54 of the actual vehicle count. Whereas, for the BCS based method the estimates are within 4.12m/s of the speed measurements and within 3.48 vehicles of the actual vehicle count. However, Table 5.1 shows that the BCS based method is computationally more efficient. This is also for the case with real data shown in Table 5.2, where we can also see the BCS based method has also given an improved estimation accuracy compared to the CS based method. In this instance for the BCS based estimates are within 7.14km/h and 22.88 vehicles of the actual measurements. Whereas, for the CS based method the estimates are within 6.85km/h and 25 vehicles of the actual traffic measurements.

5.5.2 Evaluation of Traffic State Estimation performance

Now we will consider how using estimated measurements effects the performance of estimating the traffic states within the road segments using a PF with $M_{pf} = 200$ particles. As we have previously shown that the BCS and CS based methods have a similar measurements estimation accuracy but that the BCS method is more efficient, we will only use the BCS based measurements estimation method in what follows.

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

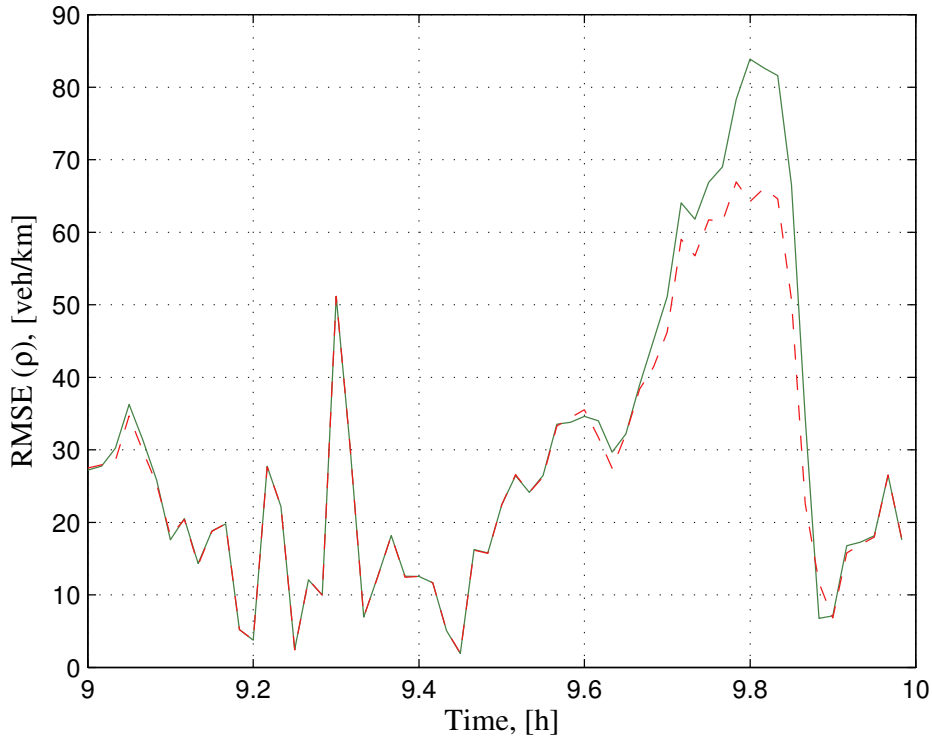


Figure 5.5: Traffic density RMSE for CLOE, the solid line is for the PF using 2 measurements only and the dashed line with the BCS estimated measurements.

The performance will be tested using the real data from Belgium over the period of an hour. We consider time steps of 10 seconds, where measurements are available every minute. The following parameters were used in the traffic model and PF: $v_{free} = 120km/h$, $v_{min} = 7.4km/h$, $\rho_{crit} = 20.89veh/km/lane$, $\rho_{jam} = 180veh/km$, $A_l = 0.01km$, $\sigma_{\xi_{Q_{j,s}}}^2 = 1$ and $\sigma_{\xi_{Q_{j,s}}}^2 = 3.24$.

Note, $r = 100$ independent Monte Carlo runs are completed. For a performance measure of the accuracy of the PF we consider the root mean square error (RMSE) as calculated in (5.38), where $j = 1$ for the speed related measurements and $j = 2$ for the number of vehicles/density related measurements. Here $\mathbf{z}_{i,k}$ is the actual measurements and $\hat{\mathbf{z}}_{i,k}$ the predicted measurements (found from traffic model and PF).

$$RMSE_{j,k} = \frac{1}{r} \sum_{i=1}^r (\mathbf{z}_{j,i,k} - \hat{\mathbf{z}}_{j,i,k})^T (\mathbf{z}_{j,i,k} - \hat{\mathbf{z}}_{j,i,k}). \quad (5.38)$$

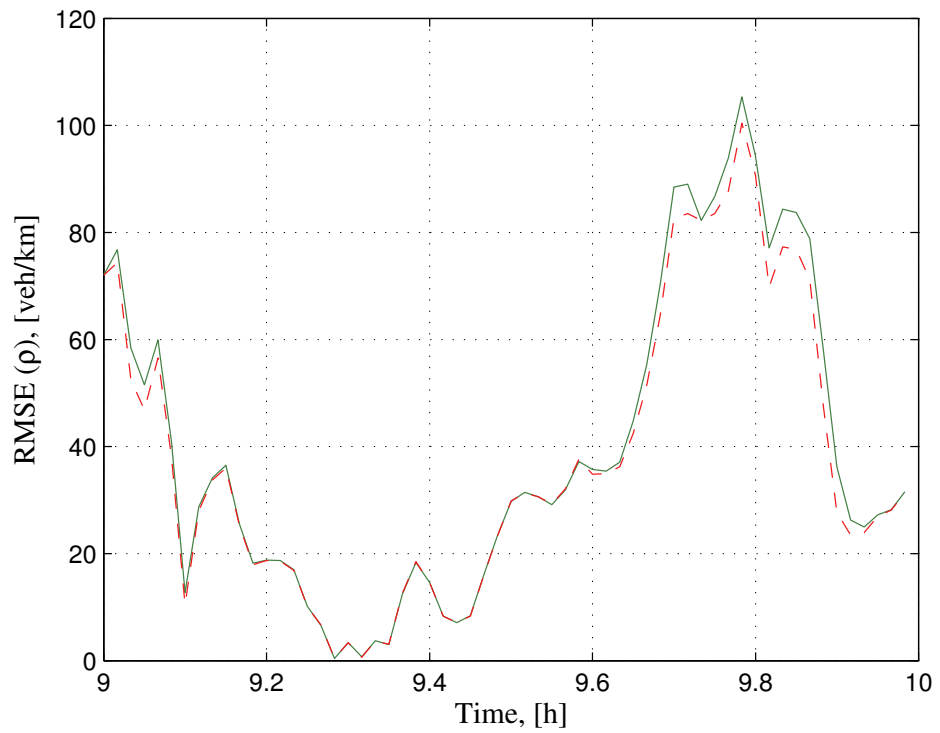


Figure 5.6: Traffic density RMSE for CLOC, the solid line is for the PF using 2 measurements only and the dashed line with the BCS estimated measurements.

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

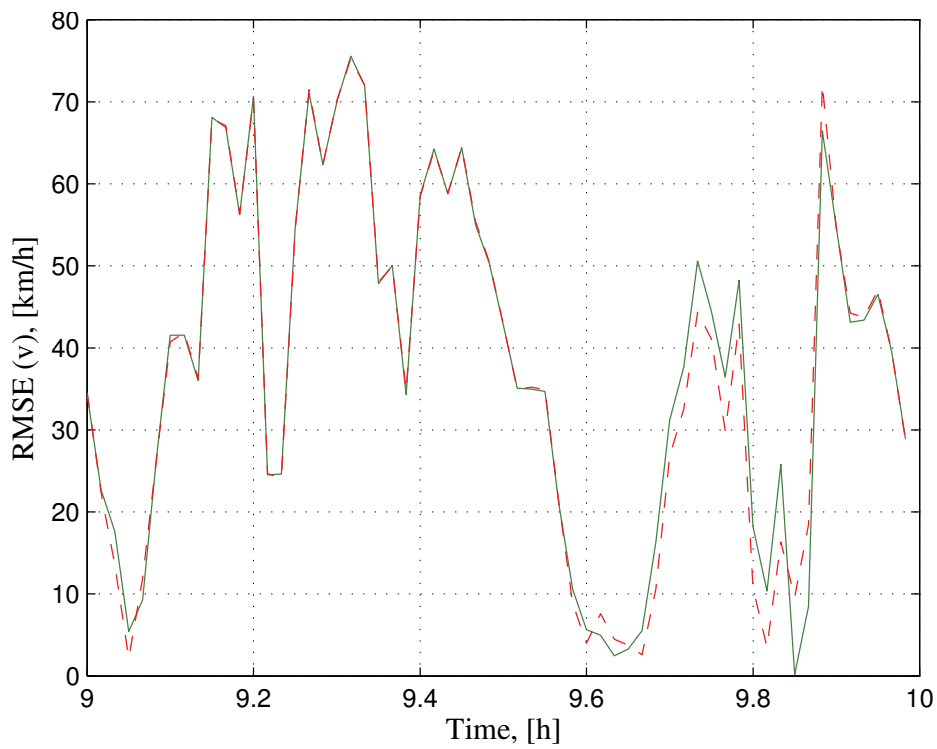


Figure 5.7: Traffic velocity RMSE for CLOE, the solid line is for the PF using 2 measurements only and the dashed line with the BCS estimated measurements.

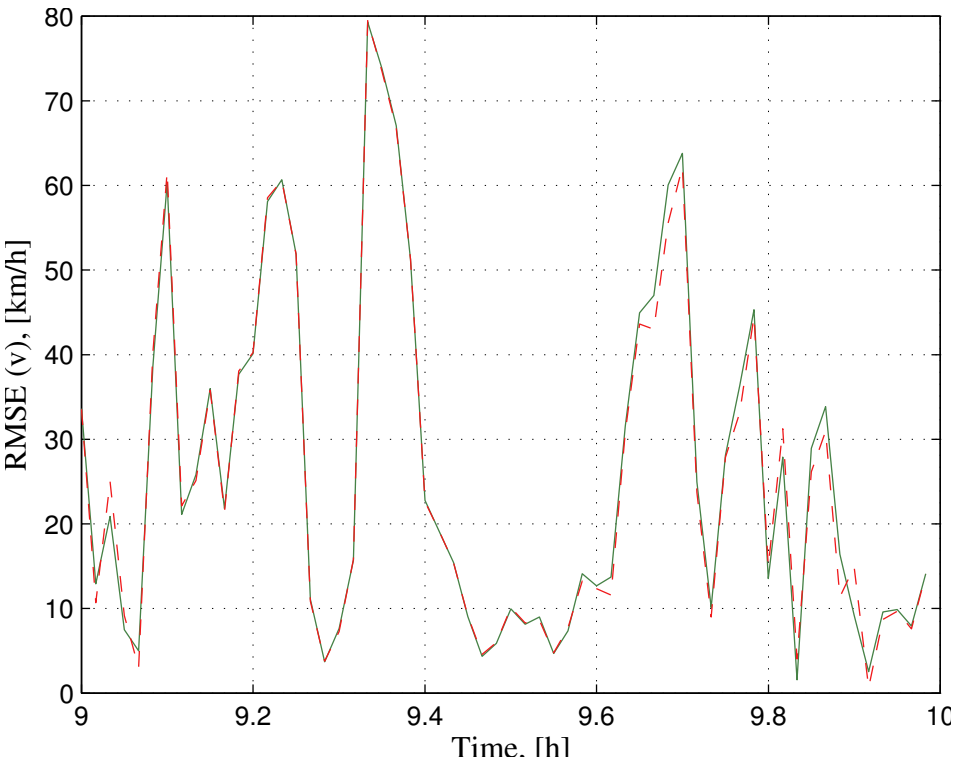
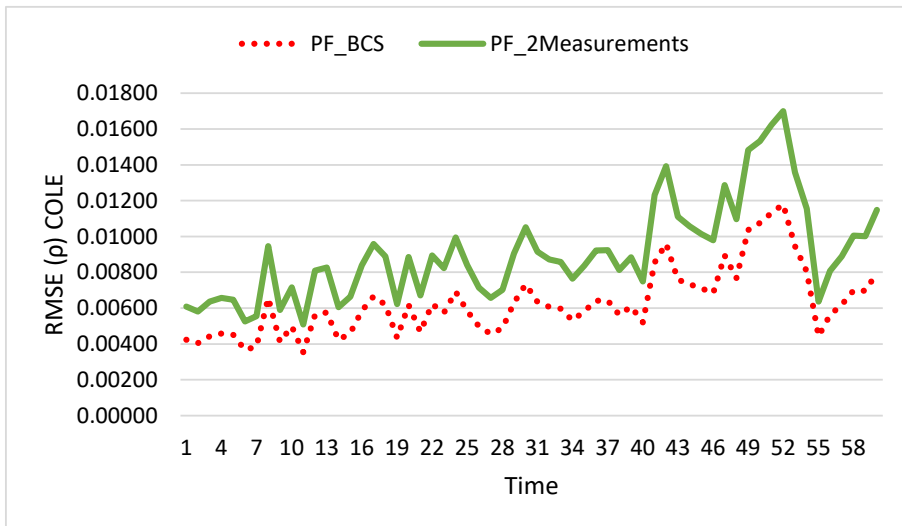
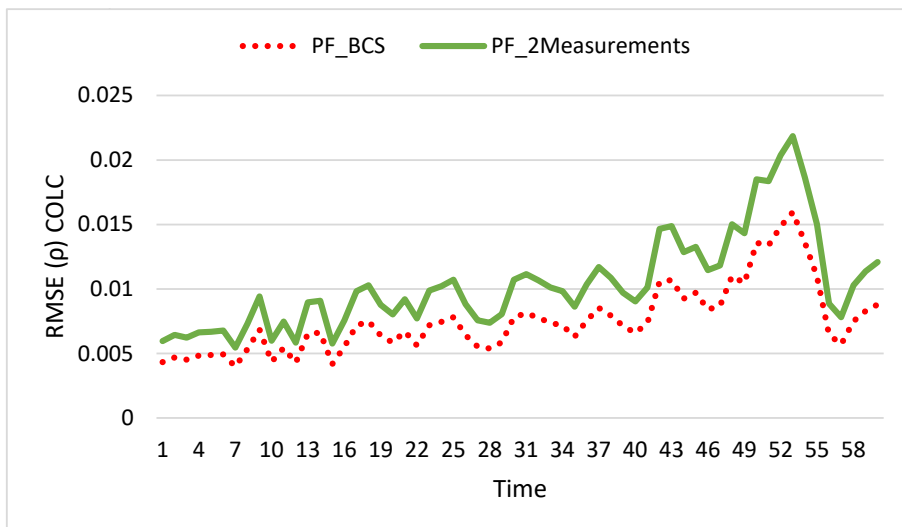


Figure 5.8: Traffic velocity RMSE for CLOC, the solid line is for the PF using 2 measurements only and the dashed line with the BCS estimated measurements.

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

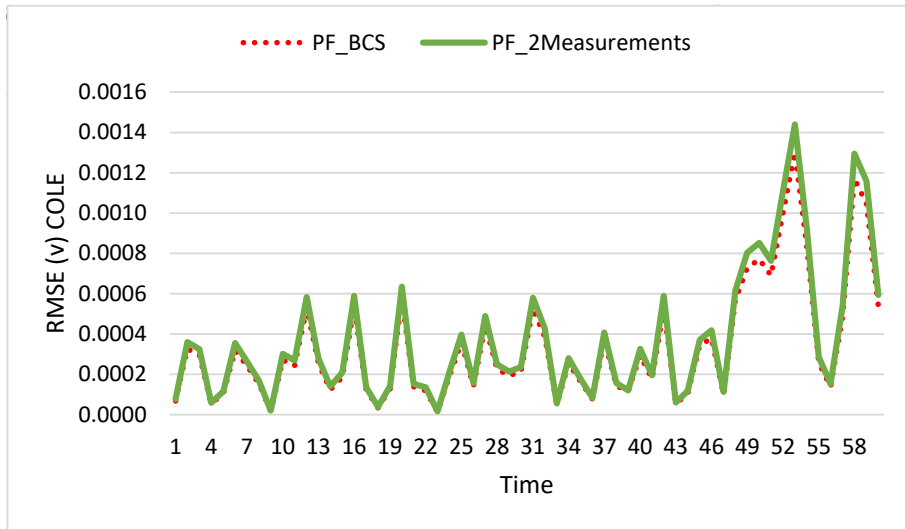


(a) Traffic density NRMSE for COLE segment.

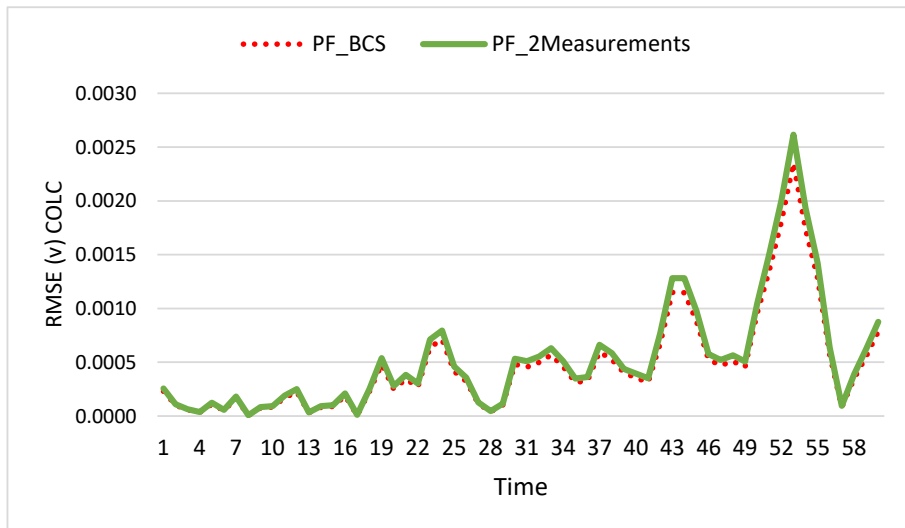


(b) Traffic density NRMSE for COLC segment.

Figure 5.9: NRMSE for the traffic density in COLE and COLC.



(a) Traffic velocity NRMSE for COLE segment.



(b) Traffic velocity NRMSE for COLC segment.

Figure 5.10: NRMSE for the traffic velocity in COLE and COLC.

5. FILTERING AND PREDICATION OF TRAFFIC FLOW

Table 5.3: Performance summary for PF with 2 measurements available and the BCS estimated measurements.

Example	2 measurements	BCS estimated measurements
Computation time (s) total (per snapshot)	6.66 (0.11)	13.28 (0.47)
\overline{RMSE}_ρ CLOE (CLOC)	29.67 (39.53)	27.51 (37.55)
\overline{RMSE}_v CLOE (CLOC)	38.11 (26.09)	37.46 (25.78)

We compare the performance for CLOE and CLOC to illustrate the effects on performance in segments where there were originally measurements available and unavailable respectively. Figures 5.5-5.8 show the changing RMSEs and Table 5.3 summarises the performances along with computation times. These show an improvement in estimation accuracy has been achieved by using the BCS measurements estimation method. This has been at the cost of a slight increase in computation time. However, the increase has not been significant enough to be a concern for real time implementation. The flow-density diagrams are plotted for the estimates from the PF with 2 measurements available and the BCS measurements available are shown in Figures 5.11-5.12. Both show the expected shape and are similar in appearance, further validating the effectiveness of the proposed method.

Figures 5.9 and 5.10 show the Normalized RMSE (NRMSE) of the traffic density and velocity in segments COLE and COLC respectively, in order to compare the performance accuracy in terms of PF with only two measurements and the PF with BCS approach. Large peaks in Figures 5.9 and 5.10 are often related to the more congested periods of time. The NRMSE is calculated as in (5.39), where $j = 1$ for the speed related measurements and $j = 2$ for the number of vehicles/density related measurements. Here $\mathbf{z}_{i,k}$ is the actual measurements and $\hat{\mathbf{z}}_{i,k}$ the predicted measurements (found from traffic model and PF).

$$RMSE_{j,k} = \frac{1}{r} \sum_{i=1}^r \left(\frac{\mathbf{z}_{j,i,k} - \hat{\mathbf{z}}_{j,i,k}}{\mathbf{z}_{j,i,k}} \right)^2. \quad (5.39)$$

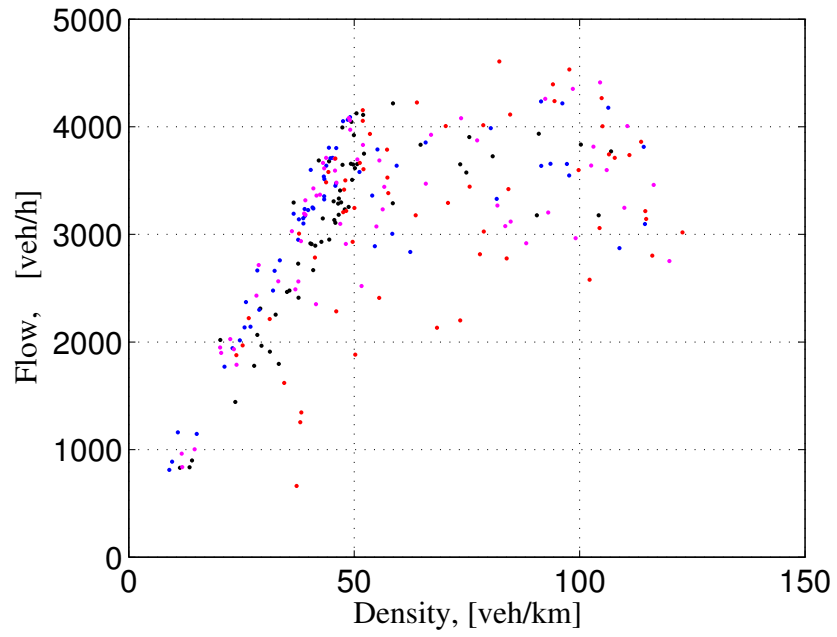


Figure 5.11: Flow-density diagram for the PF with 2 measurements available.

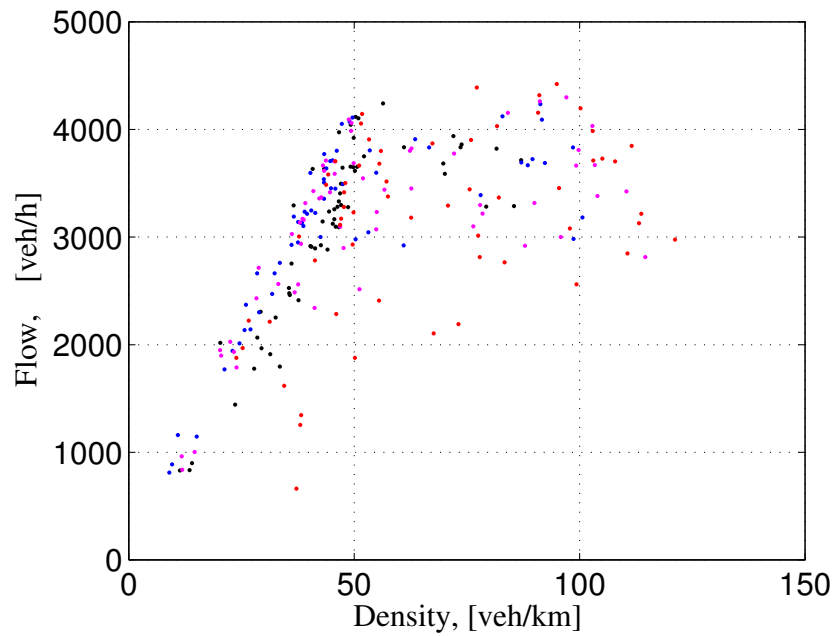


Figure 5.12: Flow-density diagram for the PF with the BCS estimated measurements.

5.6 Conclusions

In this chapter, we have proposed two solutions to the problem of missing traffic measurements. We make the assumption that the current traffic measurements will be similar to the mean of the historical measurements from a suitable period of time. This can be assured by formulating the problem as an l_1 norm minimisation which is carried out subject to ensuring the estimates give an acceptable approximation of the available traffic measurements. Then we further formulate the problem in a Bayesian framework, deriving the a posteriori distributions and marginal likelihood that are optimised using an RVM type framework. These methods can then be combined with a PF and SCM for traffic. The proposed methods are tested with simulated and real data to verify their effectiveness. We show that it is possible to get accurate estimates of the missing measurements which when used with the PF can give improved accuracy in terms of state estimation accuracy without a significant increase in computation time. For the real data considered in this thesis up to a 23.44% improvement in RMSE values has been achieved.

6.1 Conclusions

In this section, a summary of the research findings of the thesis is presented. This thesis presents a concrete, solid and logically ordered work on the research study in traffic congestion reduction in smart cities. A general introduction of traffic congestion detection, prediction and congestion avoidance methods is given in Chapter 1. Then, a detail literature review about congestion reduction in smart cities is presented in Chapter 2. Also, a general introduction of congestion, congestion detection methods, congestion notification schemes and congestion reduction approaches are given in chapter two.

In Chapter 3, a novel decentralized dynamic multi-objective optimization approach based on IoV has been proposed. This approach is called ISATOPSIS due to combines simulated annealing (SA) algorithm with the MADM TOPSIS cost function in order to provide the driver with optimal paths. This approach utilizes two attributes: the average travel speed of the traffic and the length of the road as performance criteria which allows the road to be judged under different attributes. The novelty of the proposed approach that is able to utilize the transmitted traffic information among vehicles and RSUs and react immediately in an efficient way if the traffic congestion occurs by providing the divers with new optimal routes.

This allows the driver to select the less congested path that has minimum travel time, minimum CO2 emissions and fuel consumption. Unlike the previous works where the only single objective has been utilized and the re-routing has been done based on the static information which leads to transfer the congestion to another area. The performance of the proposed algorithm is compared with three other algorithms: simulated annealing weighted sum, simulated annealing Technique for Order Preference by Similarity to Ideal Solution and Dijkstra al-

6. CONCLUSION AND FUTURE WORK

gorithm. Simulation results show that ISATOPSIS improves performance in the presence of congestion by an overall average of 19.22% in terms of travel time, fuel consumption and CO_2 emissions as compared to other algorithms.

In Chapter 4, the broadcast network in the IoV channel leads to a channel congestion problem due to utilizes only a single channel capacity among the communicated vehicles. Therefore, this thesis proposes a channel congestion control approach of IoV communication based on a non-cooperative game. Each vehicle acts as a player in the game and requests a high data rate in a selfish way. The proposed approach utilizes the sending rate of the traffic information and the vehicle priorities in order to optimize the utility function and finds the optimal sending rate. Then the optimal sending rate is distributed among the generated messages (beacon or emergency messages) based on their priorities.

Simulation results show that the GTACC has a better performance as compared to the Carrier-Sense Multiple Access with Collision Avoidance mechanism of the Wireless Access for Vehicular Environment protocol. As reported from the highway street scenario, it is shown that the proposed approach improves the QoS parameters such as throughput, average delay, number of lost packets and total channel busy time by an overall average of 50.40%, 49.37%, 58.39%, and 36.66% respectively, as compared to Carrier-Sense Multiple Access with Collision Avoidance mechanism.

another cost function has been formulated which is based on the sending rate, contention delay and priorities of vehicles in VANETs. Then, the existence of a unique Nash equilibrium is derived and the solution of the optimal game is found by using the Newton-Raphson method. Simulation results reveal that the performance of NCGACC is better as compared to NUM, GTACC and NORAC strategies, respectively. As stated from the highway scenario, it is revealed that the developed approach enhances the Quality of Service elements such as throughput, delay time, lost messages and collision probability by an overall average of 23.51%, 57.80%, 36.32%, and 35.55%, respectively as compared to, GTACC and NORAC strategies.

Unlike the previous works where suffer from commons drawbacks such as communication overhead generated due to the extra transferring of the channel information, an inequitable decline of the beacon frequency and the freezing MAC mechanism. The using of the proposed approaches in this chapter can efficiently

improve the data dissemination in the IoV networks and increase the reliability and the accuracy of the transmitted traffic information.

Finally, A traffic state estimation and prediction are given in Chapter 5. This work presents the problem of estimating traffic states within segments of the road using a particle filter and traffic measurements at the segment boundaries. When measurements are not available at all of the boundaries the estimation accuracy can decrease. We propose solving this problem by estimating the missing measurements by assuming the current measurements will approach the mean of historical measurements from a suitable time period. The proposed solutions come in the form of an l_1 norm minimization and a relevance vector machine type optimization. Test scenarios involving simulated and real data verify that an accurate estimate of the traffic measurements can be achieved and help to improve traffic state estimation accuracy of the particle filter without a significant increase in computation time.

6.2 Limitations

1. The proposed approach in Chapter 3 has few drawbacks. In order to implement the proposed approach in Chapter 3 practically, an assumption needs to be made such as utilizing a discrete measure for values of length and average speeds of the road segments. This is because of the implementation of the simulated annealing search inside the wireless sensor nodes or OBUs is very complex due to the CPU and memory limitation of sensors. Moreover, the road traffic congestion problem is a real-time processing problem. Therefore, wireless sensor nodes installed in every vehicle need to be capable to perform real-time processing.
2. The proposed approaches in Chapter 4 needs to consider more important parameters such as the propagation and queuing delay in order to effectively reduce and alleviate the wireless channel congestion. Moreover, additional information needs to be considered such as the direction, high mobility, and speed of vehicles and calculating messages priorities.
3. The approach in Chapter 5 can only be implemented for the highway roads scenarios. Therefore, for the urban scenarios, a new approach needs to be

6. CONCLUSION AND FUTURE WORK

implemented in order to find the missing measurement and increase the accuracy of the prediction.

6.3 Future Work

This section presents some of the future work that is planned:

1. The vehicle routing problem is very important in order to alleviate the traffic congestion problem and provide the drivers with the best alternative routes. This will help to improve the traffic flow and provides comfort to the drivers. In chapter 4, a decentralized approach has been developed to reduce traffic congestion in smart cities. However, future research could develop an approach that is able to integrate both the prediction of traffic congestion and routing avoidance for the drivers in order to generate robust traffic management. This can be executed by integrating the developed approach of the particle filter with Bayesian compressive sensing in Chapter 5 and the developed approach for vehicular traffic congestion avoidance in Chapter 4 in a new centralized approach.
2. Internet of vehicles have emerged as a fast-growing model, foresees all future vehicles to be connected, sharing information to improve traffic safety and convenience. However, in this network reliable data dissemination to the destination vehicles is one of the most challenges as there may be a collision in data or congestion in the network channel due to the blind broadcast of packets to their destination vehicles.

The collision in data which is called a broadcast storm or the congestion in channel leads to packets loss, redundant rebroadcast and decrease the performance of the network. The data broadcast storm and channel congestion problems in IoV networks are challenging tasks due to sharing the communication channel among communicated nodes. This makes the broadcast network only have one single capacity constraint and limited.

Therefore, adapting the data rate alone might be not enough to overcome the channel congestion and a new approach is needed which allows integrating different parameters such as sending rate, power transmission, messages

priorities and CSMA/CA elements in order to alleviate the channel congestion and improve the network performance.

3. Further channel congestion problems could be investigated in both highway and urban scenarios of the Long Term Evolution-Vehicle (LTE-V) sidelink protocol that allows the vehicles and roadside units to communicate with the e-nodes or cell towers and send the traffic data to the central traffic management server.
4. The concentration of this thesis has been on the filtering and prediction of the traffic flow on highway roads. Recently, many studies start to investigate this problem in urban scenarios by integrating the IoV concept. This includes the effect of data loss on the prediction of the traffic flow in urban roads [159], traffic flow modelling and characteristics in urban roads [160], short-term traffic flow prediction and routing avoidance based on a road to vehicle communication [161] etc. Future work could develop a new approach to deal with the missing measurements of the traffic flow on urban scenarios based on the transmitted data from the IoV.
5. Reliable traffic state estimation and prediction in smart cities at extremely Low V2X Penetration Rates.
 - Day by day, the traffic congestion of the cities is increasing due to different reasons. Some are foreseeable such as road limited capacity, peak hour, unplanned signalling and bottlenecks and others are unforeseeable due to the traffic accidents, weather situations and human behaviour. Propose a new reliable congestion estimation and prediction algorithm in vehicular ad hoc networks.
 - The proposed method considers the problem of missing data in vehicular ad hoc networks due to a high probability of lost packets in high vehicle densities.

6. CONCLUSION AND FUTURE WORK

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