DESIGN AND PERFORMANCE ANALYSIS OF POSITION-BASED ROUTING PROTOCOL USING LOCATION PREDICTION TECHNIQUES FOR VANET

Thesis

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Declaration

I hereby declare that the Research Thesis entitled **Design and Performance Analysis of Position-based Routing Protocol Using Location Prediction Techniques For VANET** which is being submitted to the National Institute of Technology Karnataka, Surathkal in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy in Information Technology is a bonafide report of the research work carried out by me. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

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Abstract

Vehicular Ad Hoc Network (VANET) is an emerging paradigm and an upcoming reality in road transportation which is designed and developed to minimize the road accidents and fuel consumption by giving a prior alert on traffic condition and collision detection using Vehicle to Vehicle (V2V) and Vehicle to Roadside Unit (V2R) communication.

VANET is said to be a subset of Mobile Ad Hoc Network (MANET) due to similar node characteristics such as self-configuring node and multihop routing for examples. Based on their similar characteristics, MANET routing protocols are used in VANET. However, at various perspectives, VANET and MANET differentiate each other such as power, speed and mobility. Hence, applicability of MANET topology based routing protocols should be re-evaluated thoroughly using IEEE 802.11p standard which is specifically designed and developed to be used with VANET communication. In addition, realistic mobility should be generated by considering urban and non-urban vehicular traffic. However, position-based routing protocols are more suitable than the topology based routing protocols as position-based routing protocols do not maintain topology of the network rather they use the vehicle position on the Earth's surface. The vehicle positions are obtained from the satellite navigation devices such as Global Positioning System (GPS), Galileo, Compass and Glonass. The position-based routing protocols use vehicle position as a *location_id* during routing. Generally, satellite obtained locations are prone to have error due to environmental effect and urban infrastructure. Due to this error, the real vehicle position would be 05-100m away from the GPS location, approximately which effect the application performance. Thus, the location accuracy of the vehicle is a prime concern in VANET which enhances the application performance of automatic parking, cooperative driving, routing etc. to give some examples. Hence, various location prediction techniques are proposed in the literature to minimize the location error.

In order to address these issues, at the outset, this thesis aims to re-evaluate the applicability of topology based routing protocols in VANET, particularly, it evaluates the Ad Hoc On-demand Distance Vector (AODV) and Optimized Link State Routing (OLSR) protocols on IEEE 802.11p standard. In the evaluation, it uses two different road network scenarios, particularly a complex road network, which represents the city road network, having multiple crossroads and an intersection of two roads.

The second contribution of this thesis aims to propose a location prediction algorithm which is designed by considering nonlinear vehicular movement, as speed of the vehicle in the city varies between 0 to 60 Km/h, due to traffic rules, driving skills and traffic density. Likewise, the movement of the vehicle with steady speed is highly impractical. Consequently, the relationship between time and speed to reach the destination is nonlinear and with reference to the previous work on location prediction in VANET, nonlinear movement of the vehicle was not considered. In addition, location error also effects the performance of position-based routing protocol in VANET. Thus, it proposes a location prediction algorithm for a nonlinear vehicular movement using Extended Kalman Filter (EKF). EKF is more appropriate contrasted with the Kalman Filter (KF), as it is designed to work with the nonlinear system. The efficacy of the prediction algorithm is evaluated on real and model based mobility traces for the city and highway scenarios. Further, prediction accuracy of the EKF is compared with the KF on Average Euclidean Distance Error (AEDE), Distance Error (DE), Root Mean Square Error (RMSE) and Velocity Error (VE) metrics.

The third contribution of the thesis proposes to use KF and EKF based location prediction techniques into the position-based routing protocol which is named as prediction based position-based routing protocol. The inclusion of KF and EKF based prediction techniques into the routing protocol has the aim to minimize the location error to improve the routing performance. The performance of the prediction based position-based routing protocol is evaluated on Two-ray ground and Winner-II propagation models with different transmission ranges of 250m and 500m for the city and highway scenarios. In simulation, two different traffic environments such as heterogeneous and homogeneous traffic are used. The performance of the prediction based position-based routing protocol using KF and EKF prediction module is compared with Cross-layer, Weighted and Position-based Routing (CLWPR) protocol on the metrics of Packet Delivery Ratio (PDR), Average Delay (AD) and throughput.

The fourth contribution of this thesis evaluates the location prediction based position-based routing protocol using KF on real time GPS traces for 500m transmission range. In addition, it evaluates KF by predicting advance location of a vehicle on a highway scenario and error removal capacity.

Based on obtained experimental results, it is observed that topology based routing protocols are less effective for VANET, while EKF based prediction is more accurate than KF based prediction. The PDR and AD got improved with EKF and KF based prediction in position-based routing protocol.

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List of Notations

Δt	Time interval
$\hat{x}_{t-1}^{-}$	Location at $t-1$
$\hat{x}_t$	Location predicted by filter at t
$\hat{x}_t^{-}$	Location predicted at t
Φ_1	Outer tire steering angle
Φ_2	Inner tire steering angle
θ	Angle of vehicle orientation
A	State transition matrix.
a	Acceleration
A^T	Transpose of A.
a_x	Acceleration towards x
a_y	Acceleration towards y
B	Model matrix
d	Distance
F_t^T	Transpose of F_t
G_r	Receiving antenna gain
G_t	Transmitting antenna gain
h_r	Receiving antenna height
H_t	Measurement matrix at t

h_t	Transmitting antenna height only in Chapter 3
H_t^T	Transpose of H_t
I	Identity matrix
K_t	Kalman gain at t
L	Loss factor
P_r	Receiving power
P_{t-1}	Error covariance at $t-1$
P_t	Estimated error covariance by filter at t
P_t	Transmitting power only in Chapter 3
P_t^-	Error covariance at t
Q	Process noise covariance
R	Measurement noise covariance
t	Time in seconds
u_{t-1}	Commanded input at $t-1$
v	Velocity
v_t	Measurement noise at t
V_m	Measured velocity
V_p	Predicted velocity
V_t^T	Transpose of V_t
v_x	Velocity towards x
v_y	Velocity towards y

w_{t-1}	Process noise at $t-1$
x	Latitude
x_0	Initial state
y	Longitude
z_t	Measured location at t

List of Abbreviations

A	AODV
A-STAR	Anchor-based Street and Traffic
AD	Average Delay
ADMR	Adaptive Demand-Driven Multicast Routing
AEDE	Average Euclidean Distance Error
AGR	Adaptive Geographic Routing
AMROUTE	Ad Hoc Multicast Routing protocol
ANN	Artificial Neural Network
AODV	Ad Hoc On-demand Distance Vector
AR	Access Router
AU	Application Unit
BPSK	Binary Phase Shift Keying
C	City
CAR	Connectivity-Aware Routing
CAVENET	Cellular Automaton based VEhicular NETwork
CBDRP	Cluster-based Directional Routing Protocol
CBR	Cluster Based Routing
CGR	Contention-based Geographic Routing
CLWPR	Cross-layer, Weighted and Position-based Routing

COIN	Clustering for Open IVC Network
CBF	Contention-based Forwarding
DDM	Differential Destination Multicast
DE	Distance Error
DECA	Distributed Efficient Clustering Approach
DLP	Destination Location Prediction
DODMRP	Destination-Driven On-Demand Multicast Routing Protocol
DR	Dead Reckoning
DSDV	Destination Sequence Distance Vector
DSR	Dynamic Source Routing
DSRC	Dedicated Short Range Communication
DVCAST	Distributed Vehicular Broadcast Protocol
EAEP	Edge-Aware Epidemic Protocol
EKF	Extended Kalman Filter
FSR	Fish-eye State Routing
GeOpps	Geographical Opportunistic Routing
GPCR	Greedy Perimeter Coordinator Routing
GPS	Global Positioning System
GPSR	Greedy Perimeter Stateless Routing
GSR	Global State Routing
GSRP	Global State Routing Protocol
GyTAR	Greedy Traffic Aware Routing

H	Highway
HARP	Hybrid Ad Hoc Routing Protocol
HyBr	Hybrid Bio-inspired Bee Swarm Routing
HyDi	Hybrid Data Dissemination
IVCAL	Inter-Vehicle Communication Assisted Localization
IVG	Inter Vehicle Geocast
JARR	Junction based Adaptive Reactive Routing
KF	Kalman Filter
LET	Link Expiration Time
LGF	Landmark Guided Forwarding
LORA	Locally Optimal Routing Algorithms
LOUVRE	Landmark Overlays for Urban Vehicular Routing Environments
LPBR	Location Prediction Based Routing
LUV	Location Update Vector
MALM	Mobility Assisted Location Management
MANET	Mobile Ad Hoc Network
MAODV	Multicast Ad Hoc On-Demand Distance Vector
MCEDAR	Multicast Core-Extraction Distributed Ad Hoc Routing
MID	Multiple Interface Declaration
MPR	Multi Point Relay
MURU	Multi-hop Routing Protocol for Urban
NLP	Neighbour Location Prediction

O	OLSR
OBU	On-board Unit
ODMRP	On-Demand Multicast Routing Protocol
OLSR	Optimized Link State Routing
PDR	Packet Delivery Ratio
PHS	Public Hot Spot
QoS	Quality of Service
RET	Route Expiration Time
RMSE	Root Mean Square Error
RO	Routing Overhead
ROVER	RObust VEhicular Routing
RREQ	Route Request
RSU	Roadside Unit
SKVR	Scalable Knowledge-Based Routing
STAR	Spatial and Traffic-Aware Routing
TBR	Tree Based Routing
TBRPF	Topology Dissemination Based on Reverse-Path Forwarding
TC	Topology Control
TIBCRPH	Traffic Infrastructure Based Cluster Routing Protocol with Handoff
TORA	Temporally Ordered Routing Algorithm
UDP	User Datagram Protocol
UMB	Urban Multihop Broadcast

V2R	Vehicle to Roadside Unit
V2V	Vehicle to Vehicle
VANET	Vehicular Ad Hoc Network
VADD	Vehicle-Assisted Data Delivery
VE	Velocity Error
VMM	Vehicular Mobility Model
VMP	Vehicular Mobility Pattern
WAVE	Wireless Access in Vehicular Environment
WSN	Wireless Sensor Network
ZRP	Zone Routing Protocol
ZoR	Zone of Relevance

Chapter 1

Introduction to VANET

Wireless communication is the cornerstone for many emerging networks such as MANET, Wireless Sensor Network (WSN) and VANET. Among these networks, VANET is an emerging paradigm which uses inter vehicular communication to establish the V2V and V2R communication among the vehicles and Roadside Unit (RSU) to minimize the accidents, traffic and fuel consumption by providing a prior alert (Boukerche 2008). In V2V communication, vehicle communicates with other vehicles either directly or through intermediate vehicles using IEEE 802.11p standard. In the latter one, vehicle communicates directly to the fixed RSU. Generally, in VANET following communication environments are found:

- Pure Ad Hoc Environment (V2V): In pure VANET, vehicle communicates to other vehicles using Dedicated Short Range Communication (DSRC) standards to send, receive and forward safety and traffic messages. In V2V communication, vehicle sensors are used to detect the events such as accidents, bad roads, ice and fluid on the road, to alert the incoming vehicles on the same road segment. V2V communication is preferred to exchange the messages in highway scenario because deployment of the RSUs on the entire road segment is not feasible now, it may get implemented in the future. Hence, V2V communication plays a noteworthy role in the highway scenario. Figure 1.1 depicts the V2V communication in the highway scenario.

- Pure Cellular Architecture (V2R): In this architecture, vehicle communicates to other vehicle using RSU which may be connected to a wireless base station to access 3G or 4G network which is used to forwards the messages to the closest base station. However, communication through 3G or 4G network is quite costly which makes it less feasible for the vehicular communication.

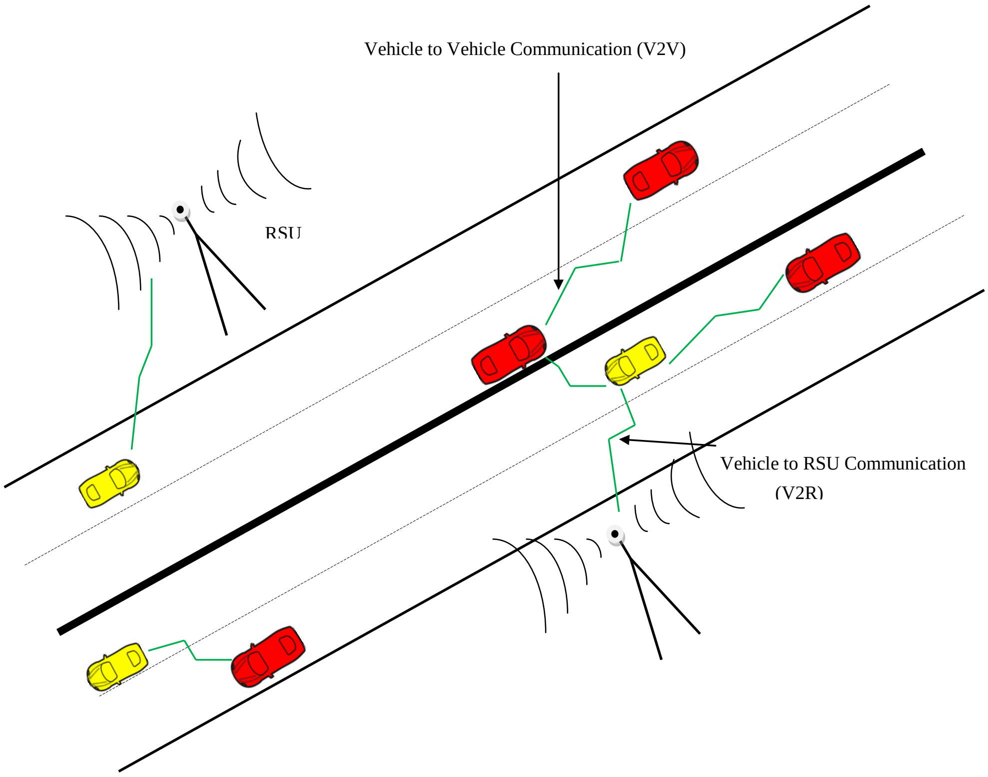


Figure. 1.1: VANET communication

- Hybrid Architecture (V2V and V2R): VANET hybrid architecture is a combination of the ad hoc and wireless network. The hybrid architecture for VANET is shown in Figure 1.1. Generally, it eases the city transportation and renders infotainment, advertisement services to the users.

Generally, a typical VANET architecture consists of the On-board Unit (OBU), Application Unit (AU) and RSU as shown in Figure 1.2 (R. Baldessari 2008). Among these devices, OBU and AU reside on the vehicle whereas RSU is fixed at the junction point or prominent places of the city. In Figure 1.2, AR and PHS are the acronyms for the Access Router and Public Hot Spot.

1.1 VANET APPLICATIONS

VANET has various applications in road transportation such as (Guerrero-Ibáñez et al. 2013):

- *Safety-based applications* infer the dangerous situation to intimate neighbor-

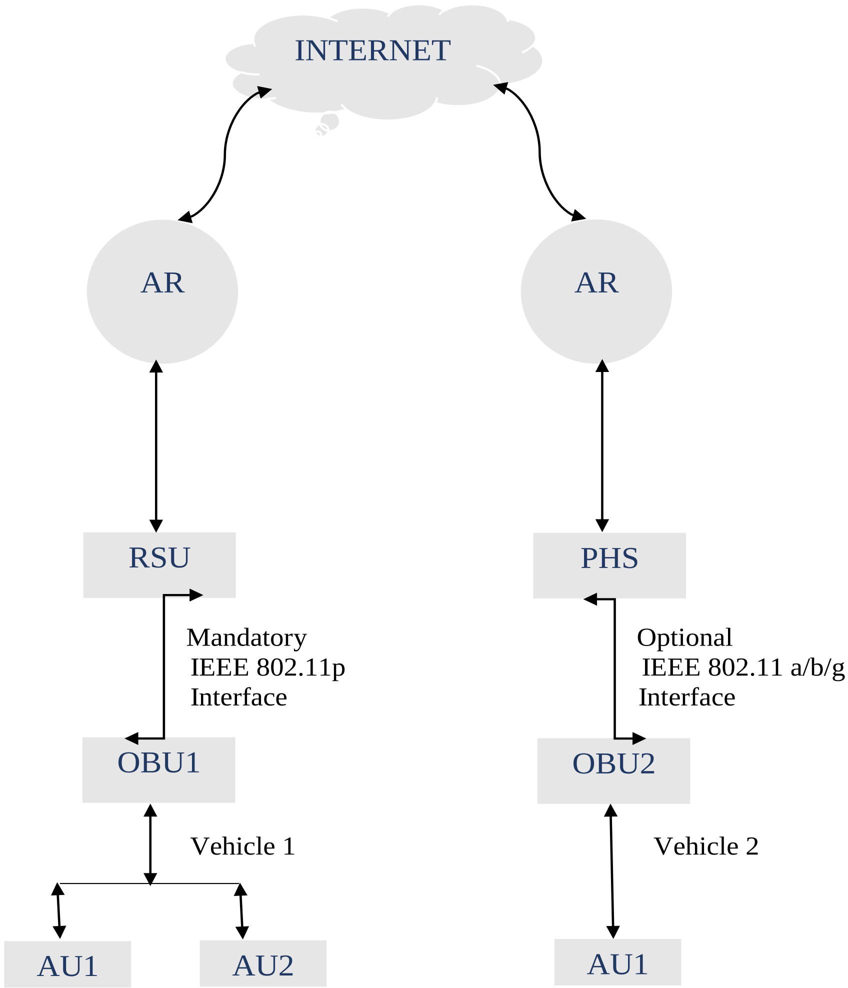


Figure. 1.2: VANET architecture

ing vehicles immediately to avoid the accidents and to minimize the collision probability with other vehicles or objects such as building, pedestrian or animals. On-board sensors are used to recognize the dangerous events and avoid it by using vehicle features such as deployment of airbag in case of collision, application of emergency brakes etc.. Such applications heavily rely on the real time information. This real time information is broadcasted to other vehicles to take an appropriate decision. For instance, real time information is required during the lane change assistance, intersection collision warning, overtaking warning, head on collision warning.

- *Infotainment-based applications* offer passenger comfort and entertainment services. For instance, on-line games and promotional messages from other commercial vehicles or restaurants. Generally, in these applications vehicle does not communicate to other vehicles except RSU. In addition, it also provides the IP-based services such as email, web access.

- *Traffic-based applications* deal with the issues related to traffic bottleneck, fuel consumption and effect on environment. In these applications RSU and sensors provide the traffic data to the central processing unit where traffic information is processed. Then, this traffic information is disseminated to other vehicles via radio broadcast. Based on this information, a driver uses the GPS and digital map to plan his trip.

1.2 DEDICATED SHORT RANGE COMMUNICATION

DSRC is also know as Wireless Access in Vehicular Environment (WAVE) which provides V2V, V2R communication using IEEE 802.11p standard. It is specifically designed and developed to be used with vehicular communication. The IEEE 802.11p standard is developed on the basis of IEEE 802.11a standard, particularly it decreases the overhead operations as compared to IEEE 802.11a (Al-Sultan et al. 2014). It is a medium of communication among the vehicles and RSU which supports from short to medium range distance. It aims to provide high data rate with low latency. DSRC channels are organized into 7 channels of 75 MHz spectrum of 5.9 GHz. Out of 75 MHz, each of the 7 channels is allocated 10 Mhz, while 5 Mhz is reserved for the guard band. Out of the 7 channels, one channel is allocated as a control channel to exchange the network control messages, while reaming channels are allocated as service channels to exchange the data packet and WAVE short messages as depicted in Figure 1.3 (Li 2012). DSRC supports up to 1000m of transmission range with 6-27 Mbps data rate.

1.3 VANET CHARACTERISTICS

In VANET, vehicles behaviour are very similar to MANET mobile nodes, thus, it is called as a subset of MANET which inherits various features such as multi-hop routing, vehicle act as a both node and router and self-configuring node. Though

	CH. 175			CH. 181		
Reserved	CH. 172 Service	CH. 174 Service	CH. 178 Control	CH. 180 Service	CH.182 Service	CH. 184 Service
5 MHz	10 MHz	10 MHz	10 MHz	10 MHz	10 MHz	10 MHz
5.850 GHz	<				>	**5.925 GHz**

Figure. 1.3: DSRC channels

the duo has some common features, however, both discriminate each other on various aspects as discussed below (Sharef et al. 2014; Boukerche 2008):

- Intermittent Network Connection: Due to the frequent changes in vehicular movement and speed, communication links get disconnected often which increases the delay and packet loss. In VANET, life of a communication link hardly exists for a short duration due to high speed and mobility. For instance, if the two vehicles have radio range of 250m and running in opposite direction with 80-100 Km/h speed. In that case, communication link hardly exists for 9.00 to 11.25 seconds. In addition, ubiquitous Internet on a vehicle is the need for VANET to offer infotainment services which is quite difficult to achieve in the current scenario, as a solution, deployment of relay node (RSU) on the road can mitigate this issue.

  With respect to MANET, nodes are bound to ply with slower speed within a confined area as compared to VANET nodes.

- Dynamism of Topology: Due to speed and movement, topology of the network get disturbed frequently, as nodes join the network and leave it quickly. Thus, topology handling in VANET is a cumbersome task for the node, in addition, it incurs routing overhead, delay and convergence time.

- Computing Power: MANET node operates on battery power which limits the computing capacity to maximize the node lifetime. Whereas, VANET node has massive computing power as it consumes the power from vehicle battery. Hence, node lifetime exists as long as vehicle exists. In addition, it can also have a large antenna, unlike MANET.

- Hard Delay: VANET communication meets hard delay to deliver the safety and traffic messages to alert the driver quickly to forbid an accident. For example, heavily congested road information need to be disseminated rapidly to forthcoming vehicle drivers. So that they can make use of an alternate path to reach the destination by choosing a less congested route. Moreover, the node should broadcast emergency messages quickly to their neighbour nodes to thwart the accidents.

- Mobility: In VANET, vehicle mobility can be predicted as vehicle movement is restricted in one direction due to road layout and traffic signs. But, MANET nodes move randomly. Nevertheless, precise forecasting of the vehicle movement is hard, since movement of a vehicle also depends on the speed of the vehicle and driver behaviour.

- Network Partitioning: Based on previous research, end-to-end connectivity is limited to short range communication, thus network partitions tend to infinite in VANET.

- Unlike MANET, VANET is a large scale network.

1.4 VANET CHALLENGES

Following are the existing challenges in VANET which need to be considered in future, while designing the routing protocol.

- Simulation: In VANET, simulation part is quite difficult as researchers need to deal with two different simulators such as network simulator and mobility simulator to evaluate the effectiveness of a model. However, network simulator is well established as compared to mobility simulator. For instance, simulating driver behaviour is quite difficult in VANET as the vehicle movement also depends on driver's decision and skills.

Table 1.1: Required location precision in VANET applications

Application	Low	Medium	High
Emergency & Safety			
Adaptive Cruise Control		✓	
Cooperative Intersection Safety		✓	
Platooning			✓
Collision Warning			✓
Blind Crossing			✓
Vision Enhancement		✓	
Services			
Routing	✓		
Data Dissemination	✓		
Accident Detection	✓		

- Localization: Satellite navigation devices, such as GPS is being used in VANET to retrieve the vehicle location information which consists of latitude, longitude and velocity information. This information is used in emergency and safety applications to improve the efficiency such as collision warning, emergency braking, automatic parking etc.. In addition, location information can also be used in service based applications.

  As accuracy of the receiver is affected by trees, lofty buildings, bridge and tunnels in the city. The accuracy of the GPS receiver is a noteworthy issue in a navigation system. In addition, other environmental factors such as line of sight, signal obstruction, fading and interference also affect the location accuracy (Li et al. 2012). In general, GPS provides the location of an object with an accuracy of 05-100m distance subject to the receiver quality. In the literature, different location prediction algorithms are proposed to compensate the location error such as dead reckoning, cellular and video/audio imaging (Qureshi & Abdullah 2014).

In VANET, location accuracy is the most critical information for some applications. For instance, emergency and safety applications need a high level of location precision, unlike service based applications. The location precision required for the few applications is outlined in Table 1.1.

- Network Partitioning: It is a major issue amid nodes are unreachable. It may occur in a sparse network or rural areas network scenarios.

- Variable Network Size: is another issue which needs to be considered while designing the medium access control protocol. For instance, in urban scenario, thousands of vehicles can be there in a small region and in such situations collision and transmission error is more likely to occur. In addition, with highway scenario, sparse network causes the intermittent connection (Cunha et al. 2016).

1.5 ROUTING IN VANET

Routing is an important component of VANET communication which facilitates to deliver the packet delivery in safety, emergency and infotainment applications. Though VANET distinguishes itself from MANET at some perspective, yet MANET routing protocols are used in VANET due to their similar characteristics. However, MANET routing protocols performance do not endure with VANET characteristics as MANET routing protocols are designed to work with the energy constraint and limited computing power system. Along with these restrictions, it also supports for the less node mobility and speed, unlike VANET. In the literature, various routing protocols have been proposed for the vehicular communication which are modified and inherited from MANET. Based on the available literature, this thesis classifies VANET routing protocols as shown in Figure 1.4 and explained as follows:

1.5.1 Uni-cast Based Routing

In uni-cast based routing, a message is delivered only to a single designated node. This routing protocol involves the intermediate node to forward the packet to the next hop if the destination node is in range of the source node, else it sends directly. The source node broadcasts the destination node address among the neighbor nodes to discover it. The uni-cast based routing protocols are categorized as follows:

1.5.1.1 Topology Based Routing

In this protocol, each node maintains the information of the neighbour nodes, a node is called as a neighbor node when it falls under the transmission range of the node. Generally, in this protocol, node searches its topology table to find the destination node or nearest neighbour node to forward the packet. If it does not find the route, it broadcasts the destination node address to all the neighbour nodes. The topology based routing protocols are classified into reactive, proactive and hybrid routing protocols (Perkins & Bhagwat 1994; Perkins et al. 2003; Nikaein et al. 2001; Johnson & Maltz 1996; Clausen & Jacquet 2003; Guangyu Pei 2000; Chen & Gerla 1998; Haas 1997; Lochert et al. 2005).

The reactive routing protocol is also known as on-demand routing protocol, wherein a node establishes a route only when it needs to send the packet. The on-demand routing protocol uses the flooding technique to discover the route when destination node address is not available in the neighbour table. Due to flooding technique, it incurs more routing overhead and delay. AODV (Perkins et al. 2003), Dynamic Source Routing (DSR) (Johnson & Maltz 1996) and Temporally Ordered Routing Algorithm (TORA) (Park & Corson 1997) are the protocols which work on the basis of on-demand routing protocol.

In proactive routing protocol, each node determines the shortest path to all the nodes in the network well in advance and the same is stored in the routing table. It updates the routing table, whenever topology change occurs. Due to frequent topology change it updates the routing table frequently which consumes more bandwidth. The routing protocols such as Destination Sequence Distance Vector

(DSDV) (Perkins & Bhagwat 1994), OLSR (Clausen & Jacquet 2003), Fish-eye State Routing (FSR) (Guangyu Pei 2000) and Global State Routing Protocol (GSRP) (Chen & Gerla 1998) are the proactive based routing protocols.

A hybrid routing protocol is an amalgamation of the reactive and proactive routing protocols. It reduces the routing overhead as hybrid based routing protocol divides the network into zones, to ease the routing process. The routing protocols such as Hybrid Ad Hoc Routing Protocol (HARP) (Nikaein et al. 2001) and Zone Routing Protocol (ZRP) (Haas 1997) are the hybrid routing protocols.

The topology based routing protocols show meager performance in VANET due to frequent topology change which incur more route convergence time, low communication throughput and delay.

1.5.1.2 Position-Based Routing

The position-based routing protocol makes use of node location obtained from satellite navigation device to identify the node on Earth's surface. Node recognizes the other node based on their geographic location and this location is used as a *location_id* in position-based routing protocol. Thus, position-based routing protocol neither supports a route table nor exchanges the routing information, albeit, it uses *location_id* in packet forwarding.

There are various position-based routing protocols proposed in the literature such as Greedy Perimeter Stateless Routing (GPSR) (B & HT 2000), Global State Routing (GSR) (Lochert et al. 2003), Anchor-based Street and Traffic (A-STAR) (Seet et al. 2004), Multi-hop Routing Protocol for Urban (MURU) (Mo et al. 2006), Connectivity-Aware Routing (CAR) (Naumov & Gross 2007), Junction based Adaptive Reactive Routing (JARR) (Tee & Lee 2010), Spatial and Traffic-Aware Routing (STAR) (Giudici & Pagani 2005) and Greedy Perimeter Coordinator Routing (GPCR) (Lochert et al. 2005). However, most of them are derived from the GPSR routing protocol. The performance of the position-based routing protocol is poor for the urban scenario due to buildings, trees and road intersections which hinder the signal propagation. However, GSR (Lochert et al. 2003), A-STAR (Seet et al. 2004), MURU (Mo et al. 2006), CAR (Naumov &

Gross 2007), JARR (Tee & Lee 2010), STAR (Giudici & Pagani 2005), GPCR (Lochert et al. 2005) tried to overcome the limitations of classical position-based routing protocol such as GPSR.

1.5.1.3 Cluster Based Routing

Cluster based routing protocol partitions the network into the clusters and selects one of the nodes from the cluster as a cluster head. A cluster head is responsible for monitoring and managing the nodes available in the cluster. Within the cluster, node communicates directly to other nodes is called as intra-cluster communication, while in inter-cluster communication, a cluster node communicates with other cluster nodes through the cluster head. The performance of the cluster based routing protocol is influenced by the selection of cluster head and cluster formation. The routing protocols such as Clustering for Open IVC Network (COIN) (Blum et al. 2003), Cluster Based Routing (CBR) (Luo et al. 2010), Cluster-based Directional Routing Protocol (CBDRP) (Song et al. 2010) are the examples of cluster based routing protocols.

1.5.1.4 Geocast Based Routing

The geocast based routing protocol adopted many features of the position-based routing protocol. It also uses the node location to establish the route. Geocast routing protocol disseminates the packet from a source node to all other nodes in a specific geographic region called as Zone of Relevance (ZoR). The nodes available in the ZoR receive the packet sent by any other node if they are in the same zone. A node located at outside of the zone does not receive the packet from other nodes which are located in different zone. When a packet reaches to the destination zone, uni-cast based routing is used to deliver the packet to the destination node. Albeit, it decides a forwarding zone which further carries the flooded packet to reduce the routing overhead and congestion. However, in this protocol, packet loss may occur if a node fails to forward the packet. In addition, network partitioning may also leads to the packet loss. The multicast services may be used by geocast based routing in a specific region (Sharef et al. 2014). RObust VEhicular Routing (ROVER) (Kihl et al. 2007), Inter Vehicle Geocast (IVG) (Bachir & Benslimane

2003), MOBICAST (Chen et al. 2009), and Contention-based Geographic Routing (CGR) (Maihofer & Eberhardt 2004) are the geocast based routing protocols.

1.5.2 Multicast Based Routing

The conventional multicast routing protocols used in wired networks are unsuitable for VANET. However, modified MANET based multicast routing protocol can be used (Muoz Muoz). Numbers of multicast routing protocols are available in the literature for MANET (Jetcheva & Johnson 2001; Souza et al. 2013; Royer & Perkins 1999; Lee et al. 2002; Yan et al. 2012; Sinha et al. 1999; Xie et al. 2002; Ji & Corson 2001). These multicast routing protocols may be suitable for the vehicular communication. The multicast routing protocols are classified into the following classes (De Morais Cordeiro et al. 2003):

1.5.2.1 Flooding

It is a simplest multicast routing protocol. In this protocol, a node floods the packet to the neighbour nodes which further forward to next neighbour node, exactly once. In a highly dense network, flooding is more feasible under the emergency situation to disseminate the packet quickly to every node. In order to avoid duplicate packet, each node maintains the information of recently received packet in the cache to deter rebroadcasting the same packet repeatedly. It removes the packet from the cache once it becomes stale. A newly received packet would be forwarded only if it is not in the cache (Viswanath et al. 2006). Although, each node receives the packet in the network, however, it incurs congestion, overhead and delay in the crowded network as each node participates in the broadcasting of a packet once.

1.5.2.2 Tree Based Routing (TBR)

Tree based routing functions either as a source based tree or shared based tree (De Morais Cordeiro et al. 2003). Source based tree builds a tree for each multicast group with shortest path and latter one builds only one tree for each group. In tree based routing, each node of a group transmits the packet using a constructed tree. The performance of TBR protocol does not endure with VANET constraint as it frequently rebuilds the distribution tree due to node mobility.

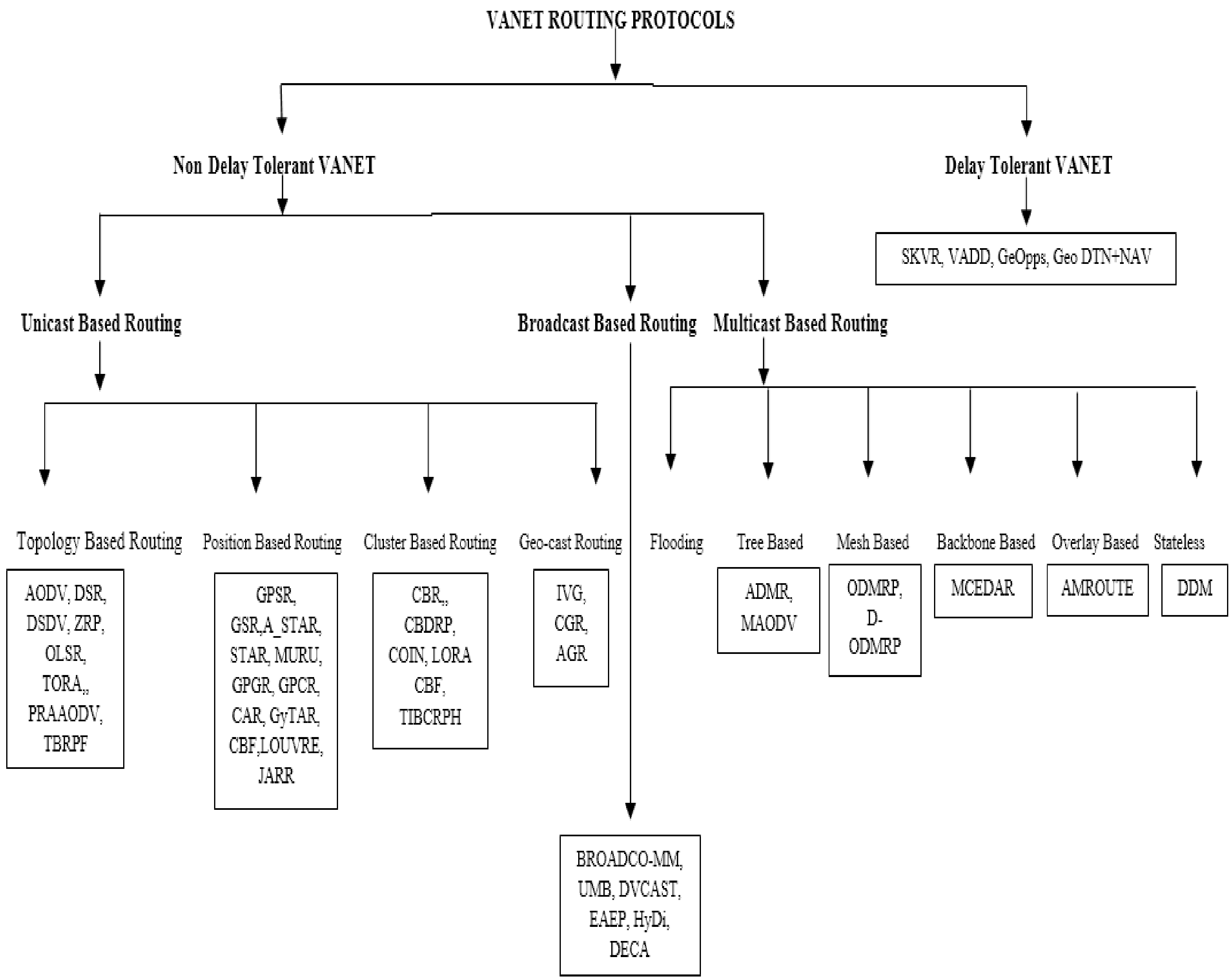


Figure. 1.4: Classification of routing protocols

In addition, it obstructs the services. Adaptive Demand-Driven Multicast Routing (ADMR) (Jetcheva & Johnson 2001), Multicast Ad Hoc On-Demand Distance Vector (MAODV) (Royer & Perkins 1999) and bio-inspired based MAODV (Souza et al. 2013) are the tree based multicast routing protocols in VANET.

1.5.2.3 Mesh Based Routing

This protocol solves the robustness problem of the tree based protocols using redundant links. Mesh based routing protocol mitigates the effect of frequent link disconnection due to topology change. This protocol performs fairly well in contrast to the tree based routing protocols. However, routing overhead and packet loss increases as network size grows (Viswanath et al. 2006). Since, it maintains multiple routes to the destination. Thus, packet gets forwarded through one of the available routes in case shortest route is unavailable, due to link failure. The On-Demand Multicast Routing Protocol (ODMRP) (Lee et al. 2002) and Destination-Driven On-Demand Multicast Routing Protocol (DODMRP) (Yan et al. 2012) are the mesh based routing protocols.

1.5.2.4 Backbone Based Routing

Backbone based routing protocol reduces the control overhead maintenance in a multicast infrastructure by introducing a simple and stable virtual backbone topology. The state information is constrained to only that node who participates in the formation of the backbone. A distributive selective approach is opted to select a core node among the nodes of the network (Muoz Muoz). It inherits the merits of the tree based routing and mesh based routing protocols. Nevertheless, backbone based routing is constrained by scalability due to the condition that traffic must pass through the backbone. The Multicast Core-Extraction Distributed Ad Hoc Routing (MCEDAR) (Sinha et al. 1999) protocol belongs to this category.

1.5.2.5 Overlay Based Routing

Tree and mesh based routing performance decreases as the number of source node increases. Moreover, control overhead and collisions are more. The overlay based routing minimizes the control overhead of maintaining state information only for multicast group members. It forms a virtual network over VANET topology between multicast group members. Virtual topology has null adaptability even underlying topology changes (Muoz Muoz). The Ad Hoc Multicast Routing protocol (AMROUTE) (Xie et al. 2002) falls under the overlay based routing. In this protocol, inefficient path creation impacts on performance.

1.5.2.6 Stateless Routing

A timely maintenance of delivery tree reduces the performance of tree and mesh based routing protocols due to brisk node mobility. A stateless routing protocol is proposed to mitigate this issue. In stateless routing, source node includes a list of destinations in the packet header. It focuses on a small multicast group and forwards the incoming packet based on destination information present in the packet header (De Morais Cordeiro et al. 2003). The Differential Destination Multicast (DDM) (Ji & Corson 2001) protocol is of this category.

1.5.3 Broadcast Based Routing

Broadcast based routing protocol is a panacea in the communication network, it delivers the packet to all other nodes present in the network. VANET exploits this classical protocol to disseminate emergency, alert, advertising and traffic packets to all the nodes. This routing protocol can also be used in route discovery procedure. Flooding is a basic method used for broadcasting a packet. Although flooding guarantees the packet delivery to all the nodes in the network. However, it incurs delay, overhead and consumes bandwidth. In addition, active involvement of the node in receiving and broadcasting of the packet leads to contention (Li & Wang 2007). BROADCOMM (Durresi et al. 2005), Urban Multihop Broadcast (UMB) (Korkmaz et al. 2004), Distributed Vehicular Broadcast Protocol (DV-CAST) (Tonguz et al. 2007), Edge-Aware Epidemic Protocol (EAEP) (Nekovee & Bogason 2007), Hybrid Data Dissemination (HyDi) (Maia et al. 2012), Distributed Efficient Clustering Approach (DECA) (Nakorn & Rojviboonchai 2010) are the protocols which work on broadcast based routing protocol.

1.6 MOTIVATION

With increasing number of vehicles and limited road infrastructure, leads to traffic congestion, more fuel consumption and fatal accidents as a consequence millions of people getting killed worldwide. The increasing number of the vehicles and their speed are the prime factor for the accidents. For instance, in India alone, 1,46,133/- accidental deaths were reported in the year 2015 which is 4.6% more from the previous year. The road transportation is not yet matured as enough as Air and Marine transport where accidents rate is almost negligible. In that context, VANET is a ray of hope to minimize the road traffic, fuel consumption and fatal accidents using V2V and V2R communication to deliver the safety and application messages to the destination in time. In VANET, position-based routing protocol plays a vital role in message dissemination accurately. Since routing protocol in VANET has its own set of challenges due to unpredictable speed and movement direction. In addition, node position obtained from the satellite system also contains an error due to environmental and technical issues which impact the routing performance such as PDR, throughput and delay. An efficient location prediction technique has potential to reduce the location error up to certain extent which will be very helpful in other applications too such as emergency and safety applications. Though many location prediction techniques and prediction based position-based routing protocols have been proposed in the literature but each of them has its own limitations. So, there is a need to devise an efficient location prediction technique and a prediction based position-based routing protocol, to improve PDR, AD and throughput.

1.7 THESIS CONTRIBUTIONS

The major contributions of this dissertation are listed as follows:

- It evaluates the applicability of the topology based routing protocols such as AODV and OLSR in VANET using city road network and single junction point on IEEE 802.11p standard.

- It proposes a location prediction technique using EKF which minimizes the location error considering nonlinear vehicular movement.

- It compares the EKF based location prediction with KF based prediction on the metrics of RMSE, DE, AEDE and VE.

- It proposes to use KF and EKF based prediction module in the position-based routing protocol to minimize the location error and to improve the PDR, AD and throughput.

- It compares the KF prediction based position-based routing protocol with other prediction based position-based routing protocols such as CLWPR and EKF based prediction based position-based routing protocols in VANET, on PDR, throughput and AD.

- It also evaluates the performance of KF prediction based position-based routing protocol with CLWPR protocol using real time GPS traces. In addition, it also evaluates the error removal capacity and advance location prediction on highway by using one time latitude and longitude, of KF.

1.8 THESIS OUTLINE

The remaining chapters of this dissertation are organized as follows:

Chapter 2 presents the existing works with respect to location prediction and routing protocols. Basically, it highlights the literature review on:

- Applicability of MANET routing protocols in VANET.

- Location prediction techniques.

- Location prediction in position-based routing protocol.

Based on literature outcomes, it defines the problem statement and research objectives.

Chapter 3 does an assessment to scrutinize the applicability of AODV and OLSR protocols in VANET with different traffic scenarios and transmission ranges on IEEE 802.11p standard. It compares the performance of the AODV and OLSR on two different road network scenarios, particularly a typical road network, which represents the city road network, having multiple crossroads and an intersection of two roads.

In Chapter 4, a location prediction algorithm is designed and developed using EKF for the nonlinear vehicular movement. It compares the performance of the proposed algorithm with KF based location prediction on RMSE, AD, VE and AEDE using real and model based mobility traces for the city and highway scenarios.

Chapter 5 proposes and evaluates the location prediction based position-based routing protocol using KF and EKF which minimizes the location error to improve PDR, AD and throughput on Two-ray ground and Winner-II (IST-WINNER 2007) propagation models for the 250m and 500m transmission range. The routing performance is measured on the city and highway scenarios using heterogeneous and homogeneous traffic environments for the variable speed, followed by performance comparison with other prediction-based routing protocol on the metrics of PDR, AD and throughput.

In addition it also evaluates the performance of the location prediction based position-based routing protocol using KF on real time GPS traces for 500m transmission range. In addition, it predicts the advance location of a vehicle on a highway by supplying one time location information and it also computes the error removal capacity of KF.

Finally, Chapter 6 provides the conclusion on the entire thesis work and future direction.

1.9 SUMMARY

This chapter introduces VANET and its role in road transportation which gives an insight on it's communication environment, characteristics, challenges, motivation and communication standard. It also classifies various routing protocols. This chapter also outlines the detailed contribution and structure of the thesis. In this thesis, location and position, prediction and estimation, vehicle and node are used vice-versa and resemble the similar meaning.

Chapter 2

Literature Review

This chapter highlights the previous works with respect to topology and position-based routing protocols and their applicability in VANET followed by location prediction techniques and position-based routing protocol using location prediction technique. Figure 2.1 shows the organization of literature review.

2.1 TOPOLOGY BASED ROUTING

This section discusses the related work with respect to topology based routing protocols. The summary of the discussion is given in Table 2.1.

Perkins & Bhagwat (1994) proposed DSDV routing protocol. This protocol is designed on the basis of link state and distance vector routing protocols of the wired network. In this protocol, each node maintains a route table which consist shortest path to the destination along with number of hops. Each row in the route table is assigned a sequence number, originated from the destination. The most recent sequence number is considered for the route selection. The downside of this protocol is packet collision and channel contention due to time synchronization among the nodes. In addition, routing overhead and congestion is more due to packet advertisement amid topology change in a large network (Perkins & Royer 1999).

Johnson & Maltz (1996) proposed DSR protocol. It is a reactive routing protocol which computes the route on-demand. Prior to communication, source node is responsible for computation of the route, it includes list of all intermediate nodes came across route discovery phase, through which packet needs to traverse back to reach the destination. Each node maintains the route cache to store the new route. The node initiates the route discovery procedure when it does not find the available route in cache. Once the route is established, node transmits the packet

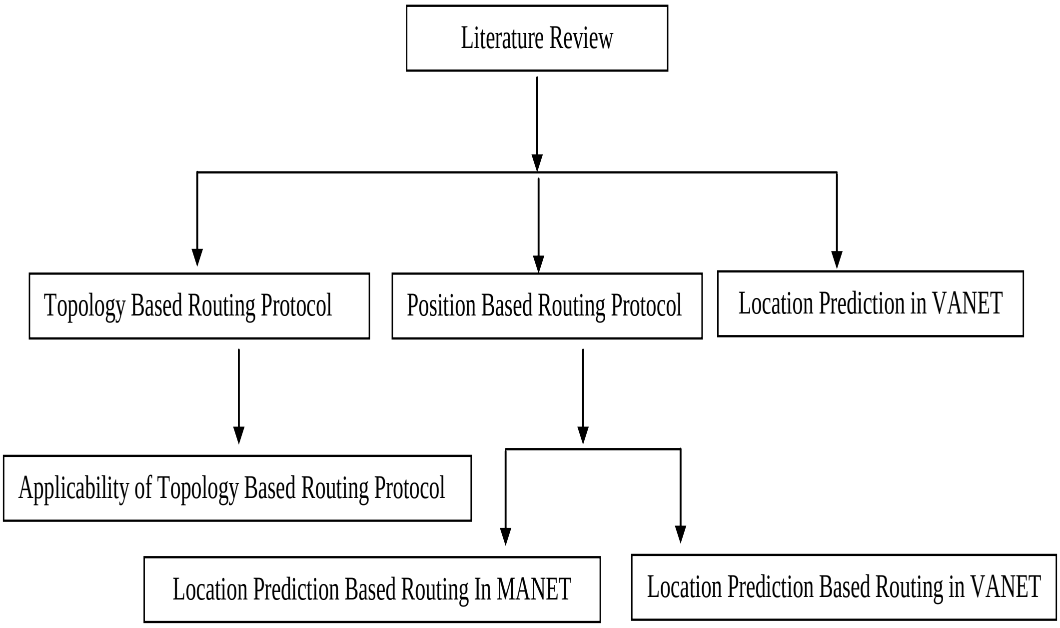


Figure. 2.1: Literature map

to the neighbour nodes as per the shortest path available in the route table. The same process is repeated by the subsequent nodes during the packet journey till it reaches the destination. It is observed that the lifetime of the route is ephemeral since nodes are mobile and routing overhead is more.

Guangyu Pei (2000) proposed a bio-inspired FSR protocol. Fish-eye captures more information about the object which is near to the focal point and it decreases as the distance between fish-eye and the object increases. Based on this theory, FSR is designed wherein a node maintains the accurate distance and quality of link for those neighbour nodes which are near. This information becomes hazy as the distance increases.

The global state routing (Chen & Gerla 1998) and FSR protocols have similar features except the fish-eye technique. Albeit, FSR reduces communication overhead during the routing process. However, mobility of the nodes affects the accuracy of route computation which is not taken into account.

As aforediscussed routing protocols use route table to maintain topology which is quite cumbersome in VANET to manage it, due to high speed and mobility.

To address these issues, Perkins & Royer (1999) proposed the AODV routing protocol. In this protocol, node neither maintains any routing information nor participates in exchange of the routing table, until node needs to communicate. A node broadcasts the route discovery packet to the neighbour nodes when destination node is not available in the neighbor table. Though using on-demand route discovery procedure, AODV minimizes the communication overhead. However, it consumes more bandwidth due to flooding of the route discovery packet. Additionally, on-demand route discovery procedure forces the packet to wait till route is ascertained. To minimize the packet waiting time amid route search in AODV, Haas (1997) proposed ZRP which combines the merits of reactive and proactive routing protocols. In ZRP, each node maintains a route table to keep topological information of the neighbour nodes present in the same zone. Consequently, nodes can communicate directly to each other if the nodes belong to the same zone, known as intra zone routing protocol. Outside of the zone, nodes communicate to other nodes using inter zone routing protocol which initiates on-demand route discovery procedure. Though ZRP uses hybrid technique to improve the routing performance by decreasing the communication overhead and latency inside a zone with the help of route table. However, outside zone communication is cumbersome due to route discovery procedure and mobility.

Clausen & Jacquet (2003) proposed OLSR protocol. In this protocol, nodes exchange the message periodically to update the network topology. Each node constructs a list of designated neighbour nodes to work as a Multi Point Relay (MPR) node and only the MPR nodes are responsible to forward the control traffic. Thus, it reduces the number of transmissions. Each node floods the packet only to the MPR nodes, which further forward the packet to the destination node by the shortest path. Though OLSR reduces the number of transmissions by restricting the broadcast only to the MPR node, nevertheless, some significant flaws are identified in it. For instance, it increases communication overhead due to periodic broadcast of *HELLO* packet to keep updated topology of the neighbour nodes. Sometime packet get diverted for a long path rather than shortest path as the forwarding decision is taken by the MPR node and most importantly it does not guarantee the loop-free routing.

Table 2.1: Summary of topology based routing protocols

Author	Protocol	Routing Mechanism	Remarks
Perkins & Bhagwat (1994)	DSDV	Based on link state and distance vector	More routing overhead and congestion
Johnson & Maltz (1996)	DSR	On-demand route computation	More routing overhead
Guangyu Pei (2000)	FSR	Based on fish eye concept	Information gradually decreases with distance
Perkins & Royer (1999)	AODV	On-demand route computation	Packet waiting time is more
Haas (1997)	ZRP	hybrid (reactive and non-reactive)	Issues with outside zone communication
Clausen & Jacquet (2003)	OLSR	Use multi point relay node	Does not guarantee loop free routing

2.2 APPLICABILITY OF TOPOLOGY BASED ROUTING PROTOCOLS IN VANET

Due to similar characteristics of MANET and VANET, MANET routing protocols are used in VANET. However, it is necessary to re-evaluate the applicability of MANET topology based routing protocols such as AODV and OLSR in VANET environment, as VANET and MANET differentiate each other at some perspective, (as explained in Chapter 1). Thus, in the literature, many previous works have been proposed which evaluate the applicability of MANET topology based routing protocols in VANET as explained in following paragraph and summarized in Table 2.2:

Clausen et al. (2002) compared the performance of the AODV and OLSR routing protocols specifically for MANET. In their work, they used IEEE 802.11 standard for communication and mobility model based on random way-point. In random way-point model, a node decides its next location and speed randomly. Henceforth, mobility obtained using random way-point model does not resemble the typical vehicular characteristics. In addition, node moves seamlessly into a region where obstacles are not considered which is quite adverse to VANET characteristics. Thus, the parameters chosen for the performance evaluation are less appropriate to test the protocols applicability in VANET. For instance, in VANET environment, the routing performance depends on several factors such as mobility, speed and consistency in network connectivity. Hence, applicability of MANET routing protocols for VANET should be evaluated only on mobility generated with VANET characteristics and communication standard.

Similarly, Haerri et al. (2006) compared the performance of the AODV and OLSR protocols for VANET on IEEE 802.11 DCF standard. To get realistic vehicular characteristics, the authors have used Vehicular Mobility Model (VMM) from VANETMOBISIM. Though the authors have taken utmost care in deciding simulation parameters. However, amid 2006 IEEE 802.11p was not in existence which is mainly designed and developed to be used with vehicular communication. In addition, in this work, which signal propagation loss model is used, is not known. It also impacts the routing performance due to signal fading in the city. Thus, chosen parameters are inappropriate to conclude the applicability of the AODV and OLSR protocols in VANET.

Khan & Qayyum (2009) assessed the performance of AODV and OLSR protocols using IEEE 802.11p standard with Nakagami fading model. The authors have evaluated the performance using city based realistic map. To get vehicular traffic, it uses MOVE and SUMO simulators. However, in simulation, it considered the uniform speed of 40 Km/h which may be insufficient to represent realistic vehicular traffic for a city as uses of constant speed makes the vehicular network more stable than the variable speed. Further, micro mobility parameters are not discussed in their work which also affect the routing performance.

Similarly, Spaho et al. (2013) compared the AODV and OLSR protocols performance on IEEE 802.11p standard for VANET. In their work, Cellular Automaton based VEhicular NETwork (CAVENET) simulator is used to generate vehicular mobility for a crossroad scenario. The CAVENET simulator does not support many essential features of VANET such as acceleration and deceleration, politeness factor and intersection management (De Marco et al. 2007). It is also found that the vehicles are distributed around the crossroad which is insufficient to assess the applicability of the AODV and OLSR protocols. In particular, in their simulation, vehicles cover each other in their transmission range as the simulation area is restricted to 200m X 200m, while vehicle transmission range is 250m. Consequently, the route discovery procedure is required only when vehicle needs to communicate with the diagonal vehicle. Accordingly, communication links do not get disconnected due to their transmission range which envelopes the entire simulation area.

Table 2.2: Summary on applicability of topology based routing protocols in VANET

Author	**Protocols**	**Comm. Standard**	**Mobility Model**
Clausen et al. (2002)	AODV, OLSR	IEEE 802.11	Random way-point
Haerri et al. (2006)	AODV, OLSR	IEEE 802.11 DCF	VMM based on VANETMOBISIM
Khan & Qayyum (2009)	AODV, OLSR	IEEE 802.11p	MOVE and SUMO
Spaho et al. (2013)	AODV, OLSR	IEEE 802.11p	VMM based on CAVENET

2.3 POSITION-BASED ROUTING

This section discusses the related work with respect to position-based routing protocols. Table 2.3 summarizes the discussion.

B & HT (2000) proposed GPSR protocol. In this protocol, each node forwards the packet using greedy and perimeter forwarding. In GPSR, each node maintains a neighbor table to store the *location_id* of those nodes which come under the radio range. Before sending the packet to the destination, primarily, a source node searches the destination *location_id* in it's neighbor table to send the packet directly, else it opts for the greedy forwarding. In greedy forwarding, a node forwards the packet to a node which is geographically nearer to the destination. If the source node does not find any of the nodes in its neighbor table, closer to the destination. Then it opts for the perimeter forwarding which forwards the packet to the next node by using right-hand rule theory which is also used when packet forwarding fails due to local maximum in greedy forwarding. A node is said to be trapped into local maximum when it realizes that a neighbor node seems to be closer to the destination but outside of its transmission range. Generally, GPSR performs better with the highway scenario while its performance is lessened in the city because of the signal obstruction. In addition, sometime perimeter forwarding forwards the packet through the long path which increases delay.

To overcome the flaws of GPSR, lee et al. (2007) proposed an enhanced perimeter routing GPSRj+ protocol. In this protocol, node forwards the packet using greedy forwarding and recovery mode. In greedy forwarding, it forwards the packet greedily along the road segment which is as close to as destination. When greedy forwarding fails to find a node closer to the destination then it opts for the recovery mode. In recovery mode a packet is backtracked along with the perimeter of the road from where it was arrived and then node looks for the next alternate junction neighbor node to forward the backtracked packet. GPSRj+ generates more delay in recovery mode as packet needs to be backtracked to the previous location to find the alternate path. When a packet is get trapped into the local maximum, GPSR and GPSRj+ both the protocols opt for the recovery mode, which increases the delay and number of hops to route a packet.

To address the GPSR and GPSRj+ issues, Seet et al. (2004) proposed an A-STAR protocol, specifically designed for the city scenario. It uses the sequence of anchor nodes deployed at the crossroad to forward the packet. A-STAR works with two forwarding modes viz. greedy forwarding and recovery mode, in latter mode packet reaches to the destination only through the anchor nodes when it is trapped into the local maximum. Though A-STAR reduces the number of hops, however, packet do not always find the optimal path and it takes more time to reach the destination.

Giudici & Pagani (2005) proposed STAR protocol to address the issues in GPSR and spatial aware routing (Tian et al. 2003) protocols. In this protocol, a node has partial information of the network around it's position. Each node maintains the traffic monitoring table and neighbor table. STAR protocol is organized in two layers, lower layer and higher layer. The former one manages and gather the information related with network status whereas latter one computes the shortest path. Node forwards the packet on a road segment where vehicle density is more. The selection of the road segment based on vehicle density may jeopardize the packet and increases the delay.

Lochert et al. (2003) proposed GSR protocol. It exploits the city map in routing process. Node floods the network with request packet containing location information of the destination. When a node finds its location similar to the location mentioned in request packet, a reply message is sent back to the source. Though GSR exploits the city map to send the packet results in more packet delay and it does not perform well in the sparse traffic. Additionally, periodic broadcast of the *HELLO* packet also increases the routing overhead. In another position-based routing protocol such as MURU routing protocol proposed by Mo et al. (2006), considers vehicle trajectory and average speed to predict the location of group of the vehicles. Among the group, available nodes act as the forwarding node between source and destination for a time period. A new metric called expected disconnection degree is introduced to evaluate the probability of a path at a predefined time. The performance of MURU protocol drops in the sparse traffic scenario as packet gets forwarded only through the intermediate nodes between source to destination.

Naumov & Gross (2007) proposed CAR protocol for VANET. CAR combines two processes together in pursuit of destination location and connected path between source to destination. In this protocol, guard nodes track the current location of the destination node even though it has travelled far distant from the initial known location. The broken links between the nodes results in more routing error which increases the delay. Similarly, Tee & Lee (2010) proposed a novel junction based adaptive routing protocol for VANET for the city scenario. In this protocol, packet get forwarded through the shortest and fastest path viz. optimal path model. Initially routing process begins with the shortest path and later shifted to the fastest path. Due to frequent broadcast of beacon the messages in sparse traffic increases the routing overhead and delay.

Bitam et al. (2013) proposed a Hybrid Bio-inspired Bee Swarm Routing protocol for Safety Application in VANET (HyBr). This protocol integrates the AODV and GPSR routing protocols. Selection of the routing protocol among these two depends on the network density. The AODV routing protocol is preferred in dense network, while GPSR routing protocol is preferred in sparse network. In this protocol, route discovery process of the AODV routing protocol is modified on the basis of bee life theory. Though it combines features of AODV, GPSR protocols and bio-inspired bee life in AODV together, standing drawbacks of AODV and GPSR protocols affect the performance of HyBR.

Jerbi et al. (2006) proposed Greedy Traffic Aware Routing (GyTAR) protocol. This protocol possess two forwarding modes viz. greedy forwarding, which forward the packet only through the junction node. When the packet get trapped into the local maximum, then it switches to the recovery mode in which node carries the packet until the next junction node or a vehicle is identified. The road junction is selected based on score assigned to it, to route the packet. To compute the score value of each junction, it considers the traffic density and curve-metric distance between the junctions.

2.4 LOCATION PREDICTION

This section discusses the state of the art with respect to location prediction technique which is summarized in Table 2.4.

Hu et al. (2003) proposed a location prediction algorithm based on adaptive KF using fading memory and variance estimation on GPS data. The fading memory approach estimates the scale factor to enhance the predicted variance component of the state, while variance estimation method directly calculates the variance fac-

Table 2.3: Summary on position-based routing protocols

Author	Protocol	Routing Mechanism	Remarks
B & HT (2000)	GPSR	Greedy and perimeter forwarding	On highway gives good performance
lee et al. (2007)	GPSRj+	Greedy and recovery mode	Generates more delay in recovery mode
Seet et al. (2004)	A-STAR	Greedy and anchor based forwarding	Does not provide optimal path
Giudici & Pagani (2005)	STAR	Greedy and traffic, neighbor table based	Increases the delay
Lochert et al. (2003)	GSR	Greedy and map based	Perform less in sparse traffic
Mo et al. (2006)	MURU	Greedy and vehicles trajectory based	Perform less in sparse traffic
Naumov & Gross (2007)	CAR	Greedy and guard nodes based	Routing error due to broken link
Tee & Lee (2010)	JARR	Greedy and shortest and fastest path based	More routing overhead and delay
Bitam et al. (2013)	HyBr	Bio-inspired AODV and GPSR	Standing GPSR and AODV issues
Jerbi et al. (2006)	GyTAR	Greedy and recovery mode	More delay

tor of the dynamic model. To measure the divergence in filtering process it uses both the method. It applies conventional KF in the absence of divergence else it opt for the adaptive KF. In their results, it is found that the algorithm performs better as compared to conventional KF. In similar work related to location prediction, Xiao et al. (2007) used grey theory model to track a target using a nonlinear system. Generally, this model is used where uncertainty and incomplete sample is available. Their prediction results are better compared to a linear system. However, in this work, it is concluded that grey theory is more appropriate for modeling the unknown part of the systems from a small number of sampling data.

Li et al. (2011) proposed mobility prediction based autoregressive *HELLO* protocol for MANET which uses auto-regression method in prediction. The node broadcasts the *HELLO* message only when difference is found between predicted and actual location, then mobility is applied by a source node and its neighbor to correct the position. Their model predicts the location of the node by considering a linear movement and mobility is predicted only when the topology is changed compared to the trajectory of the node. Similarly, Liu & Lim (2012) proposed a distributed location estimate algorithm which improves the accuracy of location prediction using cooperative inter-vehicle distance. In this work, each vehicle shares its GPS location with neighbors and each node computes the predicted location and broadcast it to the neighbor again, to recompute the final location. This algorithm is designed on the basis of GPS pseudo-range information which measures the distance between satellite and receiver. Thus, it performs better only when the signal strength is good. However, it is known that location prediction gets affected as GPS receiver could not receive the signal in the city due to trees, tunnel, buildings, fading and environmental loss (Li et al. 2014). Similarly, Drawil & Basir (2008) proposed Inter-Vehicle Communication Assisted Localization (IVCAL) algorithm for multipath environment. Basically IVCAL aims to avoid the error incurred into the location due to signal outage which is detected by a classifier. IVCAL uses KF based location prediction.

Khan et al. (2014) evaluated the positioning and tracking performance of the EKF in WSN. The algorithm performance is evaluated by using cricket sensors which computes the prediction for different models such as position model, position velocity model and position velocity acceleration model. In their results, they found that the EKF is more suitable for the localization of a node where distance measurement is affected by noise. Similarly, Chen et al. (2015) proposed a modified EKF based algorithm in target tracking of a single node in WSN when it experiences multiple dropout and insufficient anchor node coverage. They modeled the packet dropout and insufficient anchor node coverage based on two different Bernoulli random processes to see the packet arrival rate and its correctness. Based on their simulation result, author conclude that the EKF is more appropriate when communication is affected by packet drop and insufficient coverage. However, Rad et al. (2011) developed a cooperative localization algorithm for the mobile WSN using KF. Their algorithm exploits location of the anchor node to linearize the nonlinear distance measured for the location of an unknown node.

Mo et al. (2008) developed a Mobility Assisted Location Management (MALM) protocol for VANET which provides the location services to the vehicles. MALM practices the historical data and KF to compute the vehicle location. The MALM take advantage of high mobility of the vehicle to broadcast the node location information to other node and each node applies KF on received location. Consequently a node can predict the location of the other node with out any location query. Based on their theoretical analysis, MALM is able to achieve high location information with little computation overhead.

Anagnostopoulos et al. (2011) proposed a short-memory adaptive location predictor for mobile applications which predicts the location in the absence of historical mobility information. This work uses local current spatiotemporal information of the node having very less historical information. To achieve this, it designed and implemented adaptive, short-memory location predictor using linear regression model for prediction and fuzzy controller to achieve adaptation capability. Similarly, Alam et al. (2013) proposed cooperative positioning by avoiding radio ranging and range rating which fuses GPS data from different sensor sources to improve the performance of relative positioning in VANET. It shares the GPS pseudo ranges to estimate the relative position among the vehicles which are involved in communication. Their results showed 37% and 45% improvement in accuracy and precision compared to other method, respectively.

Sun et al. (2012) proposed location prediction model for VANET where vehicle does not have GPS device. Prediction of the location takes place using V2R communication and Dead Reckoning (DR) wherein initial position of the vehicle is computed by using RSU position and DR. Basically, this method is designed to be used with highway scenario. The accuracy of the model does not fit in many critical VANET applications as it achieves minimum 8.79m location error in prediction. While Fülöp et al. (2009) proposed a mobility model for the cellular network using Markovian chain on time series pattern of the mobile node. It uses the movement history of the node to maximize the accuracy compared to other prediction models.

Reza et al. (2013) used Dirichlet-multinomial model under the Bayesian estimation framework to predict the future location of a non-cooperative vehicle. Basically, this work proposed a tracking system using three different modules such as localization, tracking data collection and prediction of future positions of the target. Tracking messages are shared between RSUs and OBUs in the area where probability is more for target tracking, additionally, it also restrict on number of RSUs and OBUs involved in this operation. Similarly, Feng et al. (2015) proposed a location prediction algorithm in VANET using KF. The performance of the prediction algorithm is compared with the Artificial Neural Network (ANN) model and the results are better than ANN model. In their model, movement of the vehicle is considered to be linear. However, movement of the vehicle is linear when its speed is constant which may be possible only when vehicle is running on the highway.

2.5 LOCATION PREDICTION BASED POSITION-BASED ROUTING

This section discusses the literature review with respect to MANET and VANET routing protocols which uses location prediction technique in position-based routing protocol. The summary of the discussion is given in Tables 2.5 and 2.7.

2.5.1 With Respect to MANET

A location prediction based geographic routing is proposed by Cheng & Huang (2012) which uses prediction mechanisms on mobility information to search location services and destination node. This work involves the location prediction in

Table 2.4: Summary on location prediction

Author	Prediction Technique	Remarks
Hu et al. (2003)	Adaptive KF using fading memory	Designed for vehicle navigation
Xiao et al. (2007)	Grey theory	Designed for nonlinear movement
Li et al. (2011)	Auto-regression method	Designed for linear movement
Liu & Lim (2012)	Based on GPS pseudo-range distance	Signal obstruction due to objects
Drawil & Basir (2008)	KF based prediction	Designed for linear movement
Khan et al. (2014)	EKF based prediction	Designed for WSN
Chen et al. (2015)	Modified EKF based prediction	Designed for WSN
Rad et al. (2011)	KF based cooperative localization	Designed for WSN
Mo et al. (2008)	Uses KF along with historical data	Designed for VANET
Anagnostopoulos et al. (2011)	Linear regression model	Designed for mobile application
Alam et al. (2013)	Based on relative positioning and GPS pseudo-range	Designed for VANET
Sun et al. (2012)	Based on dead reckoning method	Designed for VANET
Fülöp et al. (2009)	Markovian chain	Designed for mobile application
Reza et al. (2013)	Dirichlet-multinomial model	Designed for VANET
Feng et al. (2015)	Based on KF	Designed for VANET

location update. It searches the destination using prediction with back-tracing and refining mechanisms. With respect to location service, each node checks the mobility information and current location in sent packet before sending the new location-update packet. In this work, location is updated using previous location and velocity of the node, in prediction equation of motion is used.

A prediction based location aided routing protocol is proposed by Doss et al. (2004) which predicts the node position within a cluster to reduce the route discovery overhead. Location prediction also help in reconstruction of the routes which establishes new routes prior to the expiry of the current route to achieve seamless communication. Similarly, Meghanathan (2008) proposed a Location Prediction-based Routing (LPBR) protocol which minimizes the route discovery and hop count overhead when the destination node is not in reach. In LPBR, when a node wants to send the data packet to such destination whose path is not known to the source, then it broadcast the route request packet. Amid broadcast each node forwards the route request packet exactly once after the addition of Location Update Vector (LUV) which consist node information such as current x-y positions, node id, velocity and angle of movement. Based on collective LUV information, a destination node predicts the topology using the equation of motion and sends back a route reply packet. The source node sends the data packet based on a path in route reply packet and it also informs dispatch time of next packet to the destination. Further, the protocol designed and developed in Meghanathan (2008) is modified to be used in multicast and multipath routing in Meghanathan (2011). Basically, it aims to lessen the tree discovery number and hop count for each source to multicast group receiver path.

Besides, Shah & Nahrstedt (2002) proposed a predictive location-based QoS routing scheme. This protocol, predicts the delay of propagation along with node location before setting up of the communication link. To determine the geographical location, location prediction is used either for intermediate node or destination node at a particular time t in future, in prediction, it uses similarity of the triangle. Whereas, propagation delay estimates the time t used in the location prediction.

In Su et al. (2001), a prediction based routing protocol is designed which uses Link Expiration Time (LET) and Route Expiration Time (RET) for an ad hoc wireless network, to minimize the effect of topology change. In prediction of LET and RET, it uses location, speed, direction and propagation range information. Since it uses GPS based location, thus, its performance may be affected in some situation such as fading, indoor location wherein GPS does not work properly.

In recent time, Cadger et al. (2016) proposes a prediction based geographic routing protocol which uses machine learning approach in prediction. This work is the extension of Cadger et al. (2012) in which machine learning and protocol implemented using MATLAB, only the mobility traces are obtained from ns-2 simulator. While in former work both machine learning and protocol implemented in ns-2 simulator. However, Cadger et al. (2012) emphasized only on location prediction using three different techniques of machine learning such as decision tree, neural network and support vector regression, unlike Cadger et al. (2016). A routing protocol proposed in Chegin & Fathy (2008), uses prediction table based on Manhattan mobility model which predict the worst-case link duration using node location. On the basis of prediction, it finds the durable paths compared to the shortest path algorithm.

A Landmark Guided Forwarding (LGF) protocol proposed by Lim et al. (2005) is designed on the basis of GPSR, basically, it reduces the impact of location inaccuracy in GPSR. It is a hybrid protocol which limits the advertisements propagation and uses location information to guide the packet when a node does not have a path to the destination. Author claims that LGF can improve upon GPSR performance by 71% with position inaccuracy of up to 200m. Similarly, Son et al. (2004) proposed Neighbor Location Prediction (NLP) and Destination Location Prediction (DLP) based GPSR protocol. NLP is designed to solve the lost link problem in GPSR, while DLP solves the loop problem. NLP estimates the current locations of the neighbor nodes amid packet route decision. Whereas, DLP helps the node to search the neighbor list for the destination node before packet forwarding decision to the destination.

For mobile underwater acoustic sensor network, Chirdchoo et al. (2009) proposed a sector-based routing with destination location prediction which uses prediction technique to predict the destination location. In this protocol, sensor nodes neither have the information about the neighbor nodes nor the topology. Though, each node knows its own position and prior information about the destination movements through assumption.

2.5.2 With Respect to VANET

Zhu et al. (2014) proposed prediction based geographic routing protocol which uses location prediction along with the buffer management and forwarding techniques. In this protocol, prediction technique is developed on the basis of speed and vehicle movement direction. It uses location history and velocity to estimate the current vehicle location. In location prediction technique, it uses equation of motion. In a similar manner, Ayaida et al. (2013) proposed a prediction-based hybrid routing and hierarchical location service routing protocol which uses the equation of motion in location prediction in greedy forwarding mode of GPSR protocol, while Zaki et al. (2012) proposed a vehicular quorum prediction based location service protocol specifically designed for the urban scenario. It uses node information such as distance to junction point and velocity, while selecting the stable location server. This protocol adopts the hybrid grey theory and alpha-beta-gamma filter in location prediction wherein node moves away from the junction point.

On the other hand, Ghafoor & Koo (2016) proposed a position-based routing protocol for cognitive radio based VANET which uses KF as a location prediction only for the highway scenario. This protocol selects the idle channel from all available channels to the vehicle on a straight road. Then it selects the best available relay node to disseminate packet to the destination. It uses KF based prediction to predict the future location of all moving vehicle, to reduce the delay.

A movement prediction in GPSR protocol is incorporated by Menouar et al. (2007). It selects the node closer to the destination as a next forwarding node. This protocol estimates the lifetime of each communication link stability then most stable route is selected based on stable intermediate link from the source

Table 2.5: Summary on location prediction used in position-based routing protocols for MANET

Author	**Prediction in Routing**
Cheng & Huang (2012)	Based on equation of motion
Doss et al. (2004)	Based on sector cluster concept
Meghanathan (2008)	Based on equation of motion
Meghanathan (2011)	Based on equation of motion (Multicast)
Shah & Nahrstedt (2002)	Based on similarity of triangle
Su et al. (2001)	Devised a prediction mechanism based on LET and RET
Cadger et al. (2016)	Based on machine learning
Chegin & Fathy (2008)	Devised a prediction mechanism based on map and Manhattan program
Lim et al. (2005)	Devised a prediction mechanism Based on topological and location information
Son et al. (2004)	Based on equation of motion
Chirdchoo et al. (2009)	Devised a prediction mechanism based on location deviation notification

to destination. It uses equation of motion in prediction to estimates the link stability. While Namboodiri & Gao (2007) proposed a reactive prediction based routing protocol which predicts the longevity of the routes and it replaces the old route by new route before it is broken viz LET. In LET prediction, location and velocity information are used. It predicts only for the highway scenario as the vehicle movement is confined to a particular direction for a long time. Similarly, Balico et al. (2015) proposed a localization prediction-based routing protocol. The node forwards the packet with predicted future location. It exploits the vehicles predicted location and digital map to forward data packet which does not need to exchange additional control messages. It compares the results with the classical flooding and simple forwarding over the trajectory algorithm.

Xue et al. (2012) proposed a prediction-based routing protocol which uses variable-order Markov model to predict the Vehicular Mobility Pattern (VMP) on real trace data. Taking the advantage of the VMP it also proposes the prediction-based soft routing protocol. In their results, for certain scenario it is found that the up to 90% and 75% overhead of control packet can be saved compared to DSR and weak state routing, respectively. Similarly, Li et al. (2009) proposed a practical location-based routing protocol to address the location inaccuracy problem and vehicle mobility, it design the location predictor to estimate the probable location of the vehicle based on location history. It uses the greedy forwarding technique in proposed routing to differentiates the packet based on distance, closer to the destination. It uses equation of motion based prediction in greedy forwarding. While Cruz et al. (2017) addresses the localization issues, it uses the unscented KF for vehicular movement and particle filter for V2V signal strength measurement. It evaluates the performance using real time GPS data of four vehicles.

Vu & Kwon (2014) proposed a mobility-assisted on-demand routing protocol to mitigate the location errors impact on routing performance. This work adopts KF based prediction to minimize the measurement location errors, in addition it estimates the link duration to lessen the overheads. Though proposed work also uses KF for error removal. However, Vu & Kwon (2014) work is different from the

Table 2.6: Summary on Difference Between Proposed Work and Vu & Kwon (2014)

Proposed Work	**Vu & Kwon (2014)**
CLWPR	AODV
Performance computed on PDR, Throughput, Delay	Performance computed on PDR, Routing overhead
It compares the KF performance with EKF.	NA
It computes the performance on real time.	NA
It computes the performance for city and highway.	NA

proposed work as listed in table 2.6.

CLWPR routing protocol proposed by Katsaros et al. (2011) is an uni-cast, multi-hop based opportunistic forwarding. It selects the next forwarding node based on the minimum weight which is calculated using Euclidean distance, angle, utilization and $\mathrm{MAC}_{\mathrm{info}}$. In this protocol, there is no provision of route discovery, thus it does not incur route maintenance cost. Each node broadcasts the *HELLO* packet periodically which consists of position, velocity and heading angle. These information are utilized in prediction of the node position. It uses $Pos_t = Pos_{t-1} + V_{t-1} * dt$ equation in prediction, where, Pos_t, Pos_{t-1} are the current and previous positions, while V_{t-1} and dt are previous velocity and time difference.

2.6 OUTCOME OF THE LITERATURE REVIEW

Based on discussed literature in Section 2.1 and Section 2.2, it is found that simulation parameters and scenarios so far used in the experiments are inadequate to test the applicability of the topology based routing protocols such as AODV and OLSR in VANET. Hence, it is required to re-evaluate the applicability of the AODV and OLSR protocols on IEEE 802.11p standard with the specific mobility generated by considering VANET characteristics such as high speed, acceleration, deceleration, politeness factor. In addition, vehicles deployment must be uneven and randomly distributed across the crossroad or on the road segment so that vehicle can communicate with the other vehicle, while moving in different location

Table 2.7: Summary on location prediction technique used in routing protocols for VANET

Author	**Prediction in Routing**
Zhu et al. (2014)	Based on equation of motion
Ayaida et al. (2013)	Based on equation of motion
Zaki et al. (2012)	Grey theory and alpha-beta-gamma filter
Ghafoor & Koo (2016)	Based on KF only for highway scenario
Menouar et al. (2007)	Based on equation of motion
Namboodiri & Gao (2007)	Based on equation of motion
Balico et al. (2015)	Based on regression forecasting problem
Xue et al. (2012)	Based on variable-order Markov model
Li et al. (2009)	Based on equation of motion
Cruz et al. (2017)	Based on unscented KF
Vu & Kwon (2014)	Based on KF
Katsaros et al. (2011)	Based on equation of motion

of the city as depicted in Figure 3.1 in which vehicles are represented by their node Id's. The geographic dimension should be enough large, while transmission range should be lesser than the geographic region to avoid the seamless connectivity.

Section 2.3 discussed the various position-based routing protocols available in the literature. Most of the position-based routing protocols are developed on the basis of GPSR protocol, thus greedy forwarding mechanism is common in all, mostly. However, it is noted that most of the routing protocol discussed in Section 2.3 did not heed on the error available in position while computing the performance. Henceforth, Section 2.4 highlights the previous work with reference to error minimization using location prediction techniques. In discussion of Section 2.4, it is found that the greater part of the work is completed with reference to WSN or MANET. As such, the research conducted for the location prediction with reference to VANET is limited.

Based on discussed literature in Section 2.4, it is concluded that an efficient location prediction algorithm can enhance the performance of VANET applications where precision of the location prediction is a prime variable. For instance, automatic parking and collision warning system require precise location prediction. Focusing beyond these applications, the performance of the position-based routing protocol such as PDR and data dissemination can also be improved by minimizing location error through prediction. In addition, position-based routing protocol performance also get influenced by the continuous change in location. For instance, Table 2.8 represents the GPS locations retrieved from OpenStreetMap (Haklay & Weber 2008) for Fig. 2.2 which covers a region of around 500x500 m^2. It is observed that the location changes as often as possible for each 200-300m circumference. These distances could be covered rapidly if the vehicle keeps running with high-speed (Raj K Jaiswal 2015). In addition, GPS locations are situated 05-100m apart from the real locations, due to error.

It is also observed that the research conducted so far towards the location prediction in VANET is done only with the linear system. The movement of the vehicle either in the city or on the highway is nonlinear as speed disruption is frequent in the city limit due to traffic, speed limit and traffic signal. For instance, a vehicle finishes 10Km distance in 26 minutes with the distinctive velocity for a particular measure of time as follows:

1. 80 Kmph for 10 minutes.
2. 60 Kmph for 2 minutes.
3. 40 kmph for 4 minutes.
4. 30 Kmph for 11 minutes.

Hence, the relationship between speed and time of the vehicle in the city is nonlinear.

In the review of literature discussed in Section 2.4, it is noted that the previous prediction algorithms did not consider the nonlinear movement of the vehicle using EKF. EKF is designed on the basis of KF to work with the nonlinear system.

It is evident from Section 2.4 discussion that the obtained location from GPS contains error and it is also known that the position-based routing protocol uses the vehicle position in routing. Hence, it is evident that the routing performance is likely to be affected by location error. Thus, it is crucial to see the effect of location prediction in routing which aim to minimize the error. Section 2.5 discuss the related work with respect to routing protocol which uses location prediction. From the discussion carried out in Sections 2.5.1 and 2.5.2, it is found that limited work is done using KF and EKF based prediction in position-based routing for VANET. In addition, it is also noted that only limited work has used real time GPS traces in performance evaluation.

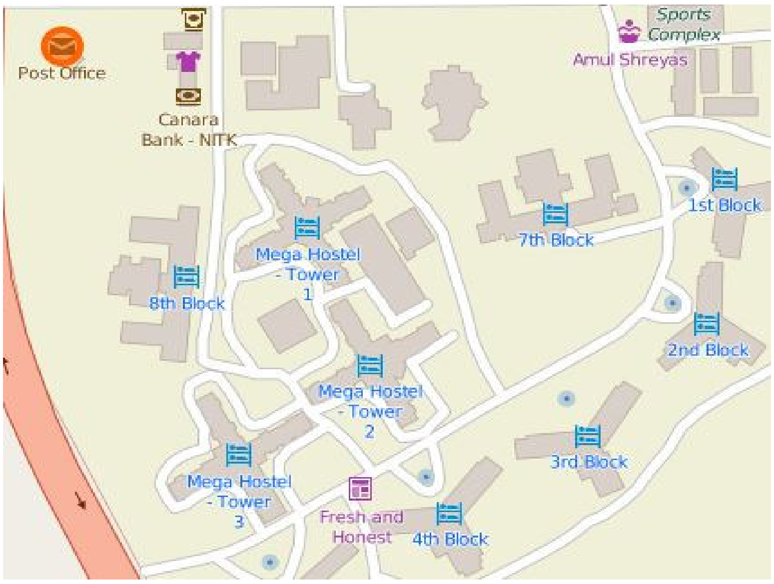


Figure. 2.2: National Institute of Technology hostel area.

2.7 PROBLEM DEFINITION

In order to address the issues and challenges as discussed in Section 2.6, there is a need to re-evaluate the applicability of topology based routing protocol from the perspective of VANET characteristics. It is also noted that there is a prime requirement to design a location prediction algorithm using EKF for a nonlinear vehicular movement by considering an appropriate vehicular model. Uses of prediction algorithm in position-based routing protocol is another prime requirement in VANET to improve the routing performance by minimizing the location error.

Table 2.8: Traced GPS coordinates

Place	Latitude	Longitude
Post Office	13.0088615	74.7933738
Canara Bank	13.0085505	74.7941301
State Bank of India	13.0089373	74.7940711
8th Block Hostel	13.0074293	74.7941167
Mega Hostel-Tower 1	13.0077351	74.7948382
Mega Hostel-Tower 2	13.0068832	74.7952084
Mega Hostel-Tower 3	13.0063213	74.7944279

Based on these facts, the research problem is defined as:
"Goal of this research work is to propose an improved/modified version of the position-based routing protocol for VANET for urban scenario. Measure the performance of the proposed routing protocol with earlier version by simulation".

2.8 RESEARCH OBJECTIVES

The research objectives are defined as:

1. Study and measure the performance of latest VANET routing protocols available in the literature. Uncover the limitations present in it and propose a modified version to overcome the observed limitation.

2. Compare the modified (proposed) routing protocol with previous version to measure the performance in terms of Packet Delivery Ratio, Average Delay, Throughput and Routing Overhead by simulation.

3. Conduct the simulation for different scenarios such as traffic types (homogeneous and heterogeneous with various speeds), different road layout, different propagation model and different node size.

4. Design a mathematical model for the proposed work.

In order to achieve the aforementioned objectives, a location prediction algorithm based on KF and EKF has been designed to be used with VANET environment. Further, KF and EKF based location predictions are used in position-based routing protocol. The performance of the proposed location prediction position-based routing protocol will be evaluated using simulation rather than real time experiment due to involvement of huge cost.

2.9 SUMMARY

In this chapter, existing state-of-the-art on topology based routing protocol, position-based routing protocol and applicability of topology based routing protocols in VANET are discussed in detail. Discussion on existing literature on location prediction algorithm for movement prediction of the vehicle by minimizing the location error are also carried out in this chapter. It also discusses the existing work with respect to location prediction based routing in MANET and VANET. Finally, open issues and research challenges in position-based routing are highlighted.

Chapter 3

Applicability of MANET Routing Protocols in VANET

Based on Section 2.1 and Section 2.2 discussions. It is found that the performance of AODV and OLSR varies in VANET/MANET due to their routing mechanism. AODV is a reactive routing protocol which computes the route on-demand while OLSR is proactive routing protocol where routes are computed prior to communication. Due to mobility and high speed routing table will be obsolete at the time of communication unlike MANET. Consequently, performance varies in VANET/MANET.

In addition, while going through the literature we found limited works were carried out with respect to applicability of these protocols. Amid literature review we found research gaps such as uses of IEEE 802.11p in evaluation which is specifically designed for VANET and came into existence by 2010-11. It is also found that very limited work has considered single and crossroad scenarios. Based on these observations, we are motivated to re-investigate AODV and OLSR routing protocols from the prospects of VANET applicability. Henceforth, this chapter re-evaluates the applicability of MANET topology based routing protocols into VANET. In this work, AODV and OLSR protocols are considered for investigation based on their proven efficiency and widely used protocols in MANET. The performance of the protocols is evaluated on IEEE 802.11p standard, with urban and non-urban vehicular traffic scenarios. The Chapter 3 is organized as: Section 3.1 discusses the experimental and simulation setup, while simulation results are discussed in Section 3.2 followed by summary of the work in Section 3.3.

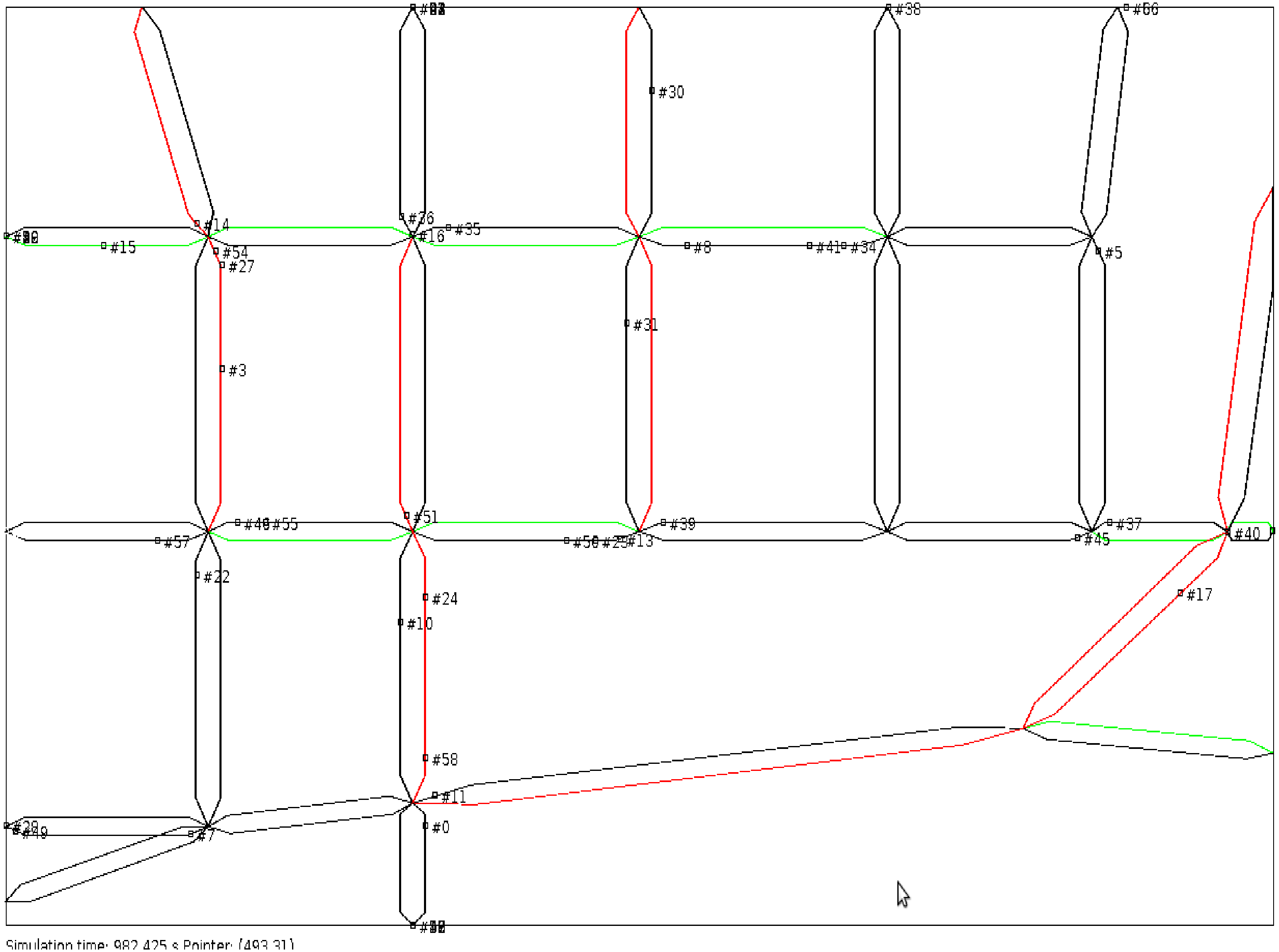


Figure. 3.1: Entire city road network

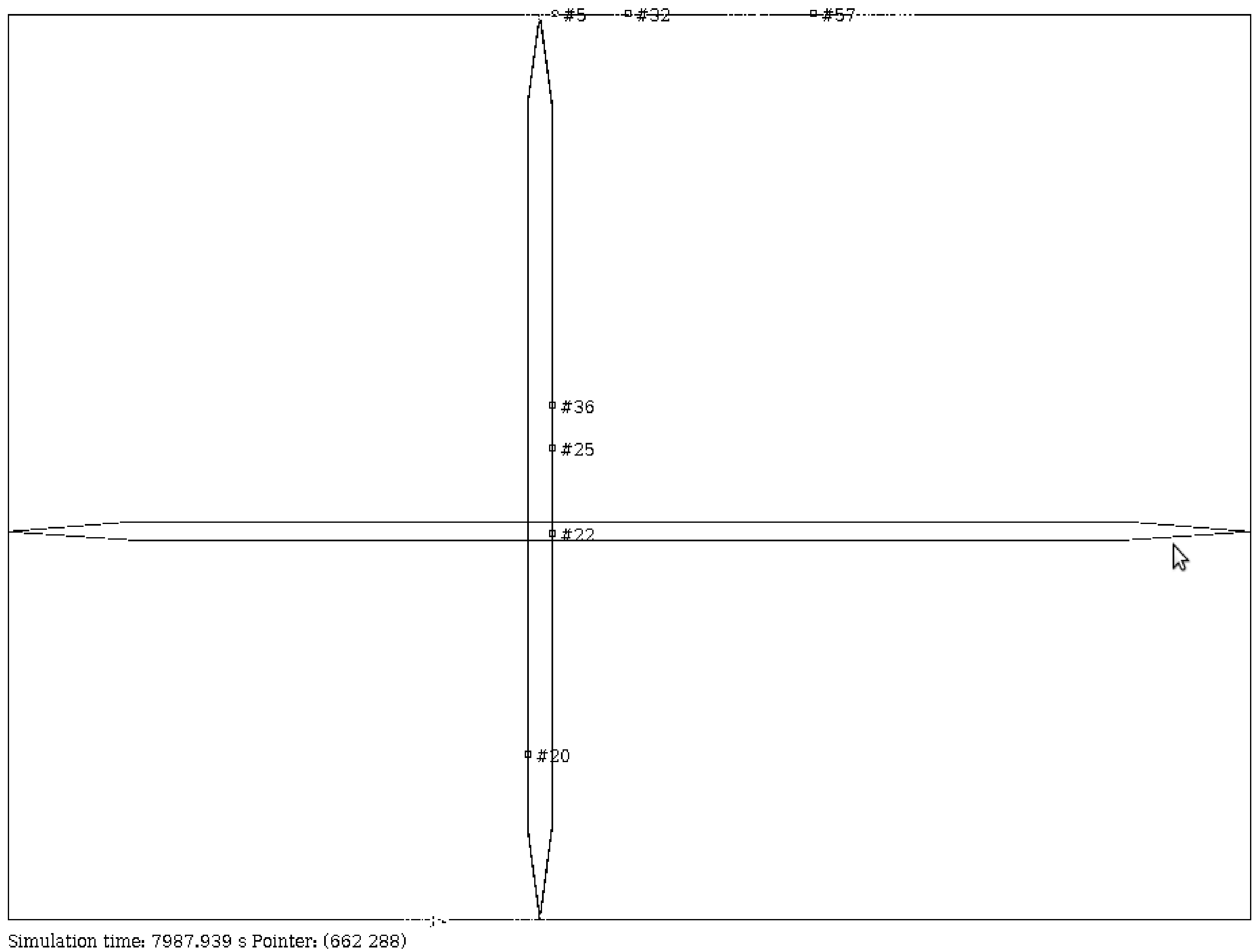


Figure. 3.2: Single crossroad

Table 3.1: Mobility generation parameters (Härri et al. 2006)

Description	**Values**
Mobility Generation Tool	VANETMOBISIM
Simulation Time (s)	499
X dim.(m)	700
Y dim.(m)	700
No. of Traffic lights	05
Traffic Light Duration (s)	60
No. of Lanes	2
Min. Speed (m/s)	0.5
Max. Speed (m/s)	35
Constant Speed	20 (m/s)
Politeness Factor for Road Segment	0.2, 0.5, 0.8
Maximum Acceleration	0.9 (m/s^2)
Maximum Deceleration	0.6 (m/s^2)
Minimum Congestion Distance	2m
Safe Headway Time (s)	2
Length of Vehicle	5m

3.1 EXPERIMENTAL SETUP AND SIMULATION

Primarily, simulation is conducted for two different city road networks, multiple crossroad and single crossroad as depicted in Figures 3.1 and 3.2, respectively. The multiple crossroad scenario depicts the typical city road topology, on which vehicles can move on any road segment and each road segment is assigned with a speed limit. Whereas, single crossroad scenario has chosen to observe the AODV and OLSR protocols performance in non-urban area over the entire city, in which nodes are located nearby. Further, each scenario is sub-divided into different transmission range of 250m and 500m. In simulation, the speed of the vehicle varies between 0 to 35 m/s randomly. In addition, performance is also evaluated considering the constant speed 20 m/s. To fix the transmission range of the vehicle, required transmission power is computed using Two-ray ground propagation model for 250m and 500m transmission range as depicted in the Equation (3.1). The Two-ray ground reflection model predicts the path losses between the transmitting and receiving antenna.

$$P_r = \left(\frac{P_t * G_t * G_r ({h_t}^2 * {h_r}^2)}{d^4 * L} \right) \tag{3.1}$$

Where, P_r=Receiving power, P_t=Transmitting power, G_t=Transmitting antenna gain, G_r=Receiving antenna gain, d=Distance, L=Loss factor, h_t=Transmitting antenna height, h_r=Receiving antenna height. The height of antenna is set to 1.5m for both transmitter and receiver and loss factor is assumed to be 1 in Equation (3.1). Mobilities are generated for 15, 30, 45 and 60 nodes using VANET-MOBISIM which is an extension of the CANU Mobility Simulation Environment (CanuMobiSim), a flexible framework for user mobility modeling. CanuMobiSim is a Java based simulator which generates vehicle movement traces in different formats for different network simulators for mobile networks such as NS2/NS3, GloMoSim and QualNet. The VanetMobiSim generates the vehicular mobility considering realistic automotive motion models at both macroscopic and microscopic levels. Further, Nodes are deployed randomly in 700mx700m simulation area for each scenario. In first scenario, some of the crossroads are equipped with traffic lights with 60 seconds duration as depicted in Figure 3.1, whereas, in second scenario only single crossroad is used which is also equipped with traffic light as shown in Figure 3.2. Each road segment is divided into two lanes, which are categorized into the fast and slow moving lane. The intelligent driving model with intersection management controls the movement of the vehicle such as acceleration and deceleration according to the front moving vehicle or traffic lights, including driver behaviour during the overtake using politeness factor. It also includes a safety gap of 2m between two vehicles to keep the safe distance and safe headway time in mobility. In order to solve the contention issue, only 50% of the nodes communicate. In addition, it is also taken care in simulation that

Table 3.2: Protocol parameters considered for test scenario (Perkins et al. 2003; Clausen & Jacquet 2003)

AODV	**OLSR**
Active Route Timeout=10s	Willingness=3
Hello Interval=1s	Hello Interval=2s
Allowed Hello Loss=3 Pkts	TC Interval=5
Net Diameter=5	MID Interval=5
Node Traversal Time=30ms	
RREQ Retries=3	

nodes communicate to other nodes at different timings which also minimizes the effect of contention. Table 3.1 represents the mobility parameters considered in the simulation. This work used the AODV protocol available in NS-2.35, whereas OLSR protocol is incorporated in NS-2.35 using UM-OLSR patches. Parameters of the both protocols are kept as per the standards as defined in their RFCs and depicted in Table 3.2. The simulation is also conducted for the different data generation rate such as 512, 1024, 1536 and 2048 Kbps for each category to observe the protocols behaviour with respect to data rate. Table 3.3 contains the list of parameters used in NS-2.35.

3.2 EXPERIMENTAL RESULTS AND ANALYSIS

The AODV and OLSR performances are only evaluated for V2V communication and it is compared on the performance matrix of PDR, routing overhead, throughput and average delay, respectively. Primarily, results are obtained for two different scenarios such as 250m and 500m transmission range which is further divided into variable and constant speed. The results are also computed to examine the behaviour of AODV and OLSR protocols with respect to data transmission rate for the city scenario. Each simulation for different scenarios are carried out for multiple times to get the average results. With reference to the statistical computation such as confidence interval it is found that we need at least 20-30

Table 3.3: Network simulator parameters (Haerri et al. 2006)

Parameters	**Values**
Network Simulator	NS-2.35
Simulation Time (s)	499
Routing Protocols	AODV and UM-OLSR
Antenna Model	Omni-Directional Antenna
Modulation Technique	BPSK
Radio Propagation Model	Two-ray ground
Transmission Range	250m, 500m
MAC Type	IEEE 802.11p
MAC Rate	2 Mbps
Interface Queue Type	50
Transport Protocol	UDP
Data Type	CBR
CBR Generation Rate (Kbps)	512, 1024, 1536, 2048
Packet Size	512 Bytes
No. of Connections	50% of Number of Vehicles
No. of Vehicles	15, 30, 45, 60
Vehicle Density	$\#vehicles.(\pi.range^2/x_{dim}.y_{dim})$

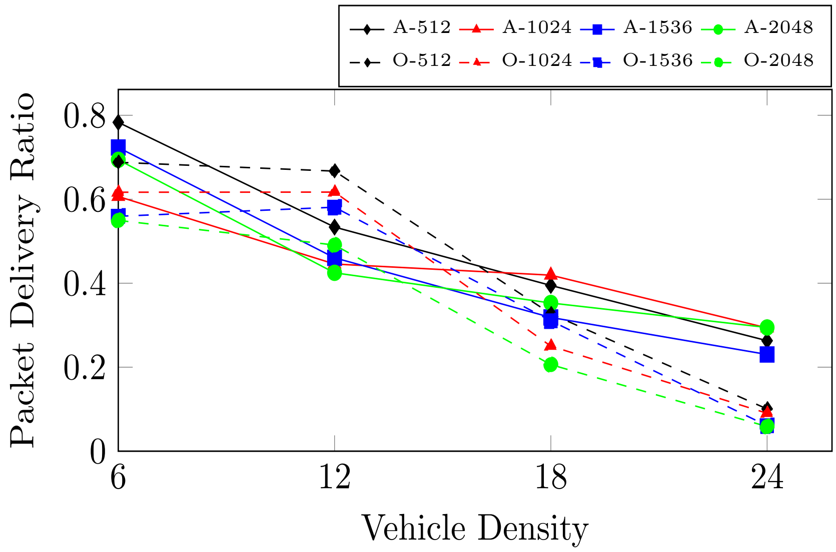


Figure. 3.3: Packet delivery ratio for the city road network (250m)

times simulation run for a single scenario to generate the population size which will be used to calculate either of 90%, 95% and 99% confidence level. From the population size we select 30%-40% simulation result for sample size which is used in calculation of mean and variance value. This is possible when we are doing

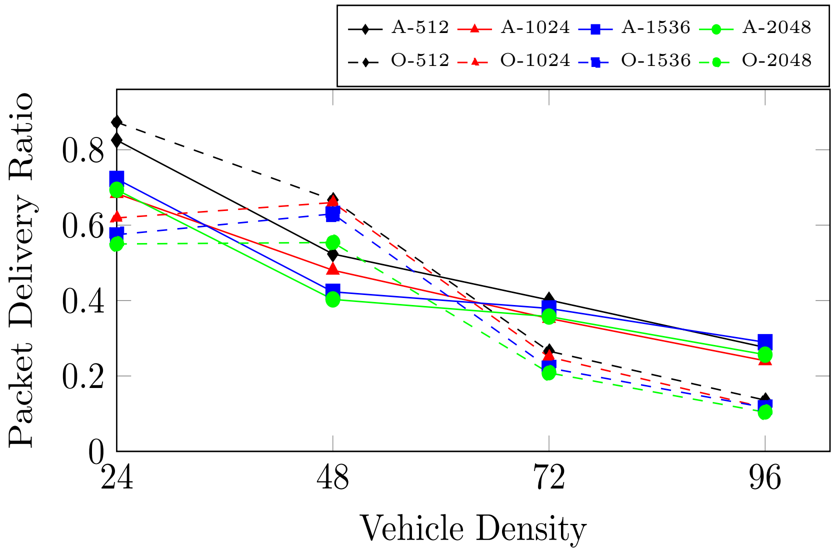


Figure. 3.4: Packet delivery ratio for the city road network (500m)

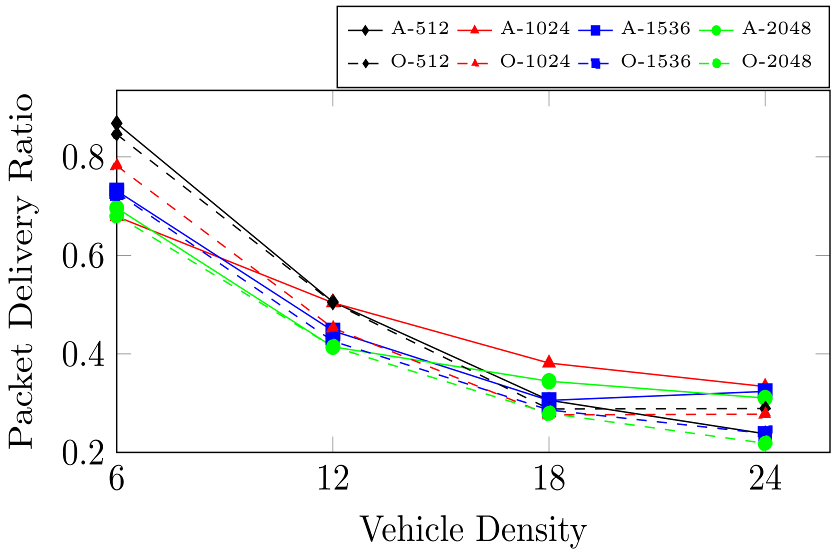


Figure. 3.5: Packet delivery ratio for single crossroad network (250m)

evaluation with 5-10 nodes for 10-30 seconds of simulation run. Based on this we found that the current work is an extensive work where simulation time is 500 seconds and minimum simulation running time is 20 minutes for 15 nodes which goes up to 1 days for 60 nodes. Henceforth, in this work confidence interval is not considered. In results the abbreviation A and O are used for the AODV and

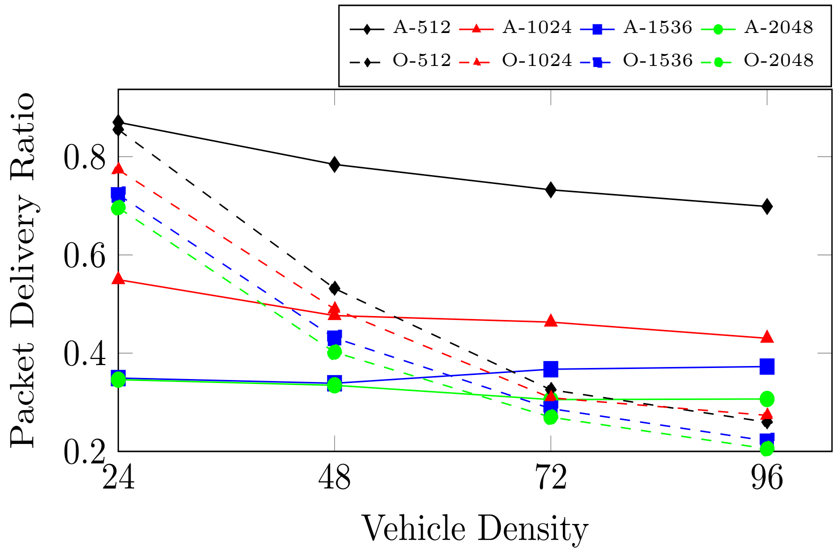


Figure. 3.6: Packet delivery ratio for single crossroad network (500m)

OLSR protocols, respectively. The individual performance analysis with respect to PDR, routing overhead, throughput and average delay are discussed as follows:

3.2.1 Packet Delivery Ratio

PDR is the ratio of total number of packets received and sent by the destination and source, respectively, which is very much dependent on number of vehicles, data generation rate and transmission range. Generally, transmission range makes the network sparse and dense based on its range. For instance, with 250m transmission range less number of vehicles will be covered compared to 500m, consequently, 250m will have sparse network scenario while 500m will have dense network. Based on simulation area transmission range has been fixed, if we increase the simulation area then transmission range has to be increased. The results of PDR are explained as follows:

Figures 3.3 and 3.4, show the PDR performance with respect to vehicle density. From the results, it is clear that the AODV protocol outperforms as compared to OLSR protocol in 250m transmission range for the entire city road network. It achieves 78% PDR for 250m transmission range at 512 Kbps data generation rate.

Whereas OLSR protocol does better as compared to AODV protocol with 500m

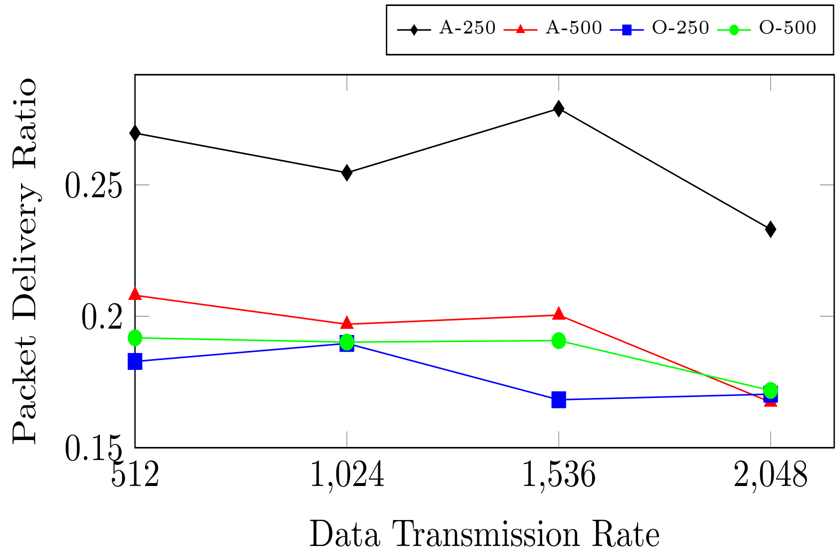


Figure. 3.7: Packet delivery ratio with respect to data transmission rate for constant speed (city)

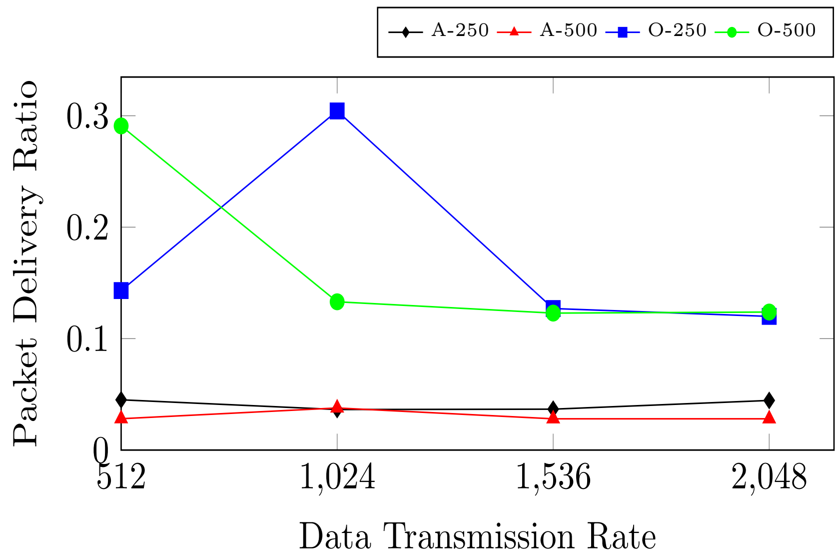


Figure. 3.8: Packet delivery ratio with respect to data transmission rate for variable speed (city)

transmission range, due to availability of route in route table, while AODV needs to discover the route more frequently with more number of vehicles in 500m transmission range. It achieves 82% PDR with respect to 512 Kbps data transmission rate. PDR marginally increases in the single crossroad scenario to 84% with respect to OLSR protocol on 512Kbps, whereas AODV protocol reaches 81% for 250m transmission range. However, their performances are much closer to each other with respect to 500m transmission range as shown in Figures 3.5 and 3.6. Nevertheless, OLSR protocol has slight stable performance compared to AODV protocol.

With reference to data transmission rate for the city scenario, AODV proto-

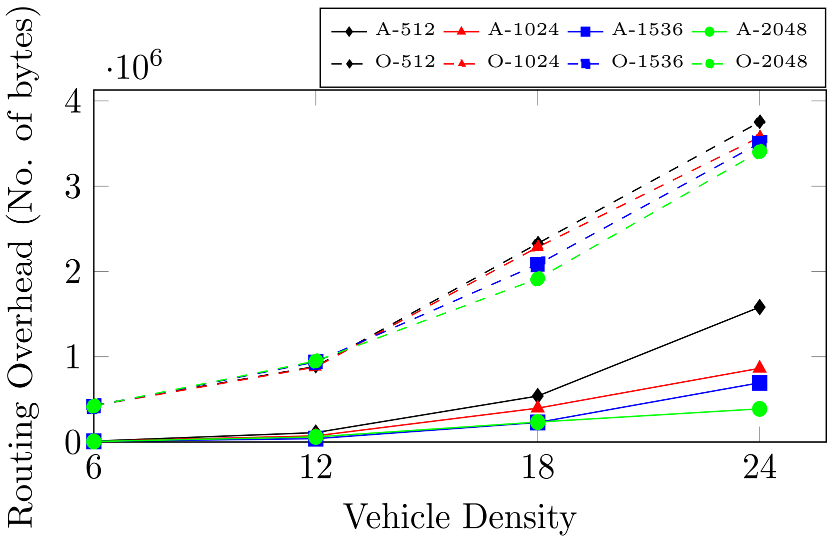


Figure. 3.9: Routing overhead for the city road network (250m)

col has better PDR than OLSR protocol with constant speed of the vehicles for the both transmission range, as constant speed makes the network stagnant and stable topology which increases the longevity of the communication link. In addition, AODV does not need to process the route discovery procedure. Whereas this performance results get reverses in favour of OLSR protocol with variable speed. From the results, it can be observed that the route table maintenance does favour to OLSR protocol in variable speed situation and it gets affected with the constant speed, unlike AODV protocol. It is also observed that both the protocols PDR decrease when data transmission rate increases. Overall, both the protocols have poor PDR with respect to data transmission rate as shown in Figures 3.7 and 3.8. However, from Figures 3.7 and 3.8 it is observed that AODV has highest

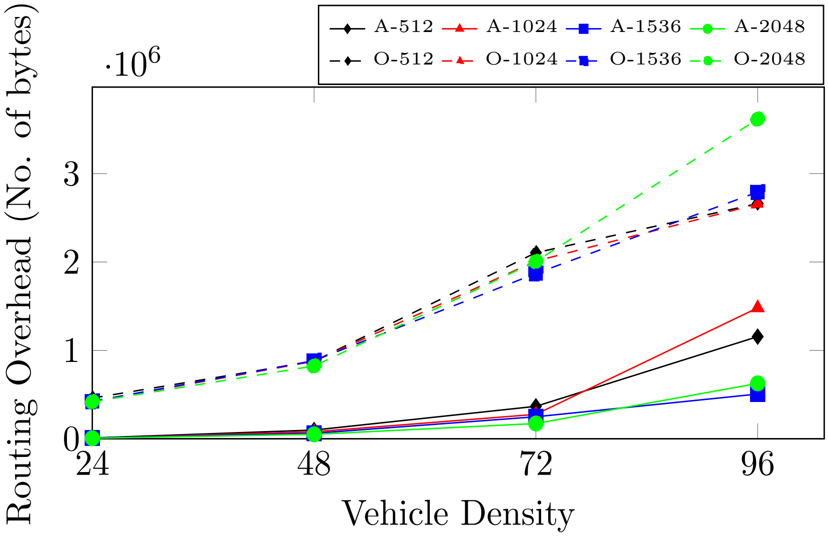


Figure. 3.10: Routing overhead for city road network (500m)

at 1536 data transmission rate for the constant speed, while OLSR has highest PDR at 1024 data transmission rate for variable speed, due to less congestion at that instant. Though AODV and OLSR protocols achieve acceptable PDR with 512Kbps data rate. However, PDR of both the protocols decreases as the vehicle density and data generation rate increases.

Overall in all the scenarios, vehicle mobility increases packet drop with more number of vehicles and data generation rate, which infuse more number of packets in network. Hence, OLSR and AODV protocols could not achieve acceptable PDR for high vehicle density and data transmission rate which is a prime requirement to disseminate the safety messages in a critical situation in VANET.

3.2.2 Routing Overhead

Routing overhead represents the number of bytes required to construct and maintain the routing table. In this work, all the control packets such as *HELLO*, *RREQ* and *RREP* are considered, while computing the routing overhead, packet bits are converted into bytes rather than number of packets. Among these, some packets are broadcasted to each node such as *HELLO*, *RREQ* which increase the routing overhead. The size of *HELLO* packet does not change in AODV protocol throughout the simulation, while the size of *HELLO* packet increases due to topology control message which is the part of *HELLO* packet in OLSR protocol. For instance, AODV protocol has 44 bits for *HELLO* and RREP packets and 48 bits for *RREQ* packet. Whereas in OLSR protocol, *HELLO* packets have 48, 116, 160 bits and it further changes according to the size of topology control message which is the main reason for having more routing overhead as compared to AODV.

From the results, it is observed that OLSR protocol has quite high routing overhead, due to route table maintenance, with the city road network at all level of data transmission rate. It increases as the vehicle density increases in both the transmission range. The routing overhead in OLSR protocol increases due to the maintenance of routing table which is heavily suffered by the topology change. Whereas, AODV protocol has less routing overhead compared to the OLSR protocol in the city road network due to reactive nature. However, in AODV protocol, routing overhead increases exponentially as the vehicle density increases, while it decreases as the data transmission rate increases as shown in Figures 3.9 and 3.10.

With reference to single cross road scenario, OLSR protocol has more routing overhead which is very much similar to the entire city road network. Intuitively, from Figures 3.11 and 3.12, it can be concluded that data transmission rate does not much effect the routing overhead for OLSR protocol with 250m and 500m transmission range. Whereas, AODV protocol has less routing overhead compared to OLSR protocol in the city road network. It is more improved with 500m range as node covers more number of nodes in its proximity. However, routing overhead is maximum at 72 vehicle density due to unreachable destination as shown in Figure 3.12. It is also observed that routing overhead computed for entire city road network and single crossroad are different. The AODV protocol has highest routing overhead with respect to data transmission rate for 250m transmission range on constant speed as the node covers less number of nodes in its proximity. It is improved drastically when the transmission range increases to 500m, while routing overhead is keep on decreasing as the data transmission rate increases. The OLSR protocol has 12.74% less routing overhead on an average than the AODV

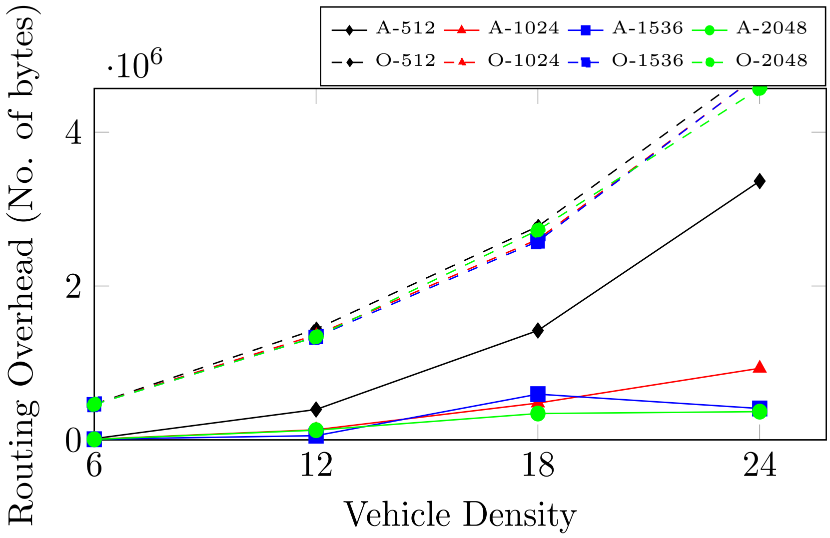


Figure. 3.11: Routing overhead for single crossroad network (250m)

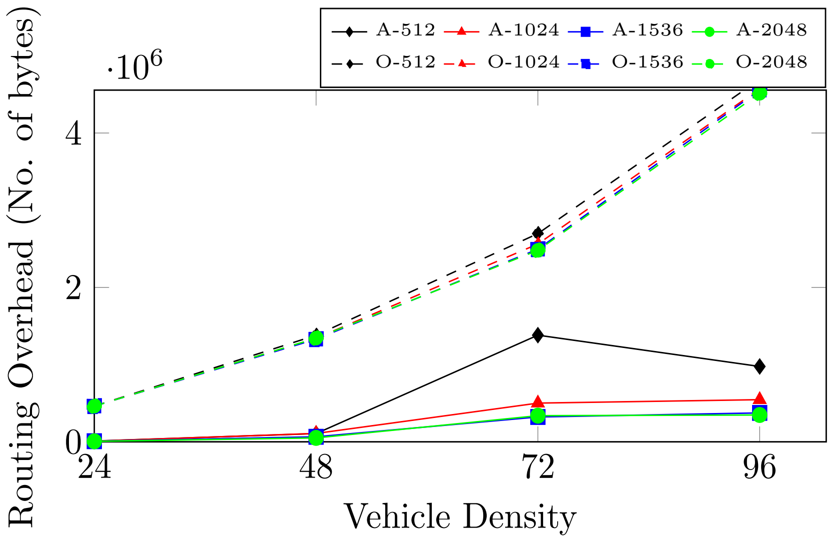


Figure. 3.12: Routing overhead for single crossroad network (500m)

protocol with respect to 250m transmission range, due to unreachable destination, whereas AODV protocol does better than OLSR protocol with 500m transmission range.

With reference to variable speed, OLSR protocol has 29.8% more routing overhead on an average than the AODV protocol in both transmission range as topol-

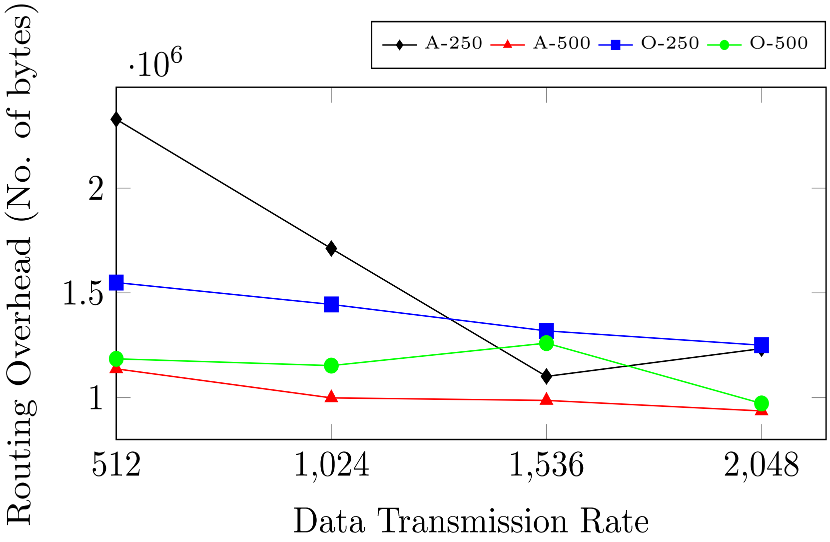


Figure. 3.13: Routing overhead with respect to data transmission rate for constant speed (city)

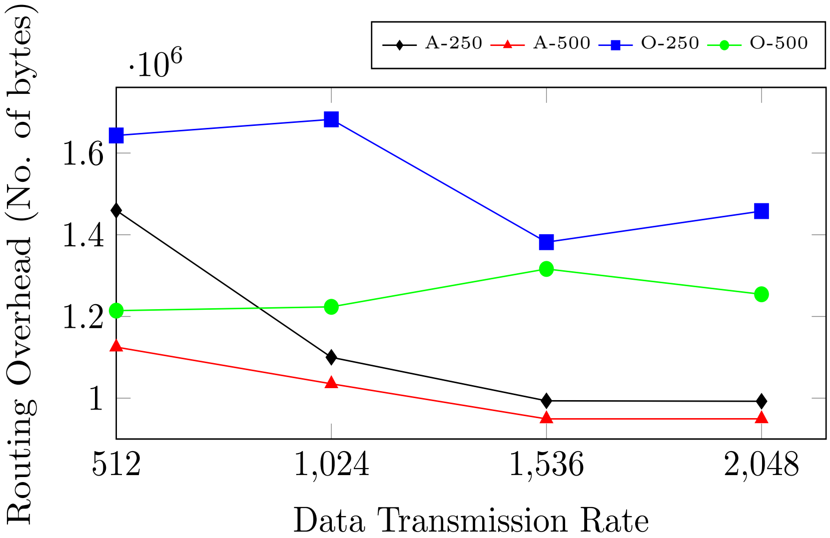


Figure. 3.14: Routing overhead with respect to data transmission rate for variable speed (city)

ogy of the network changes frequently which sometime causes sudden rise and fall in performance. The OLSR protocol has quite unpredictable routing overhead with respect to data transmission rate unlike AODV protocol wherein routing

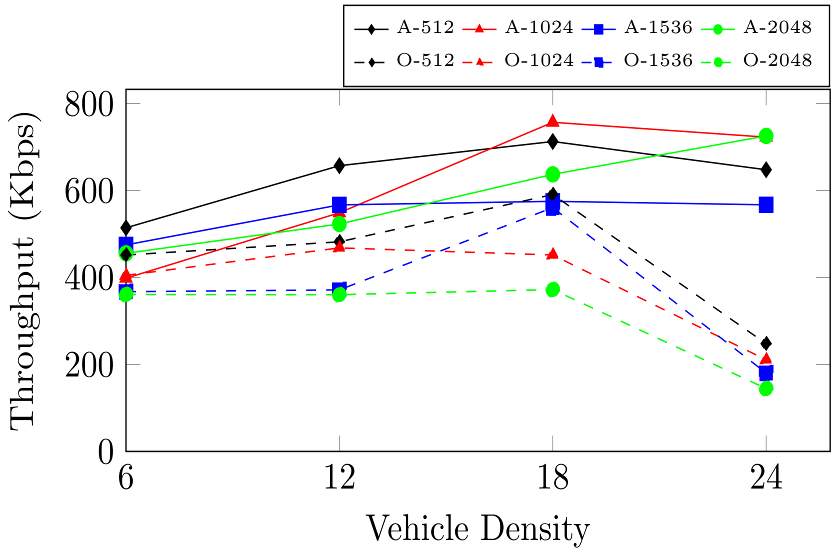


Figure. 3.15: Throughput for the city road network (250m)

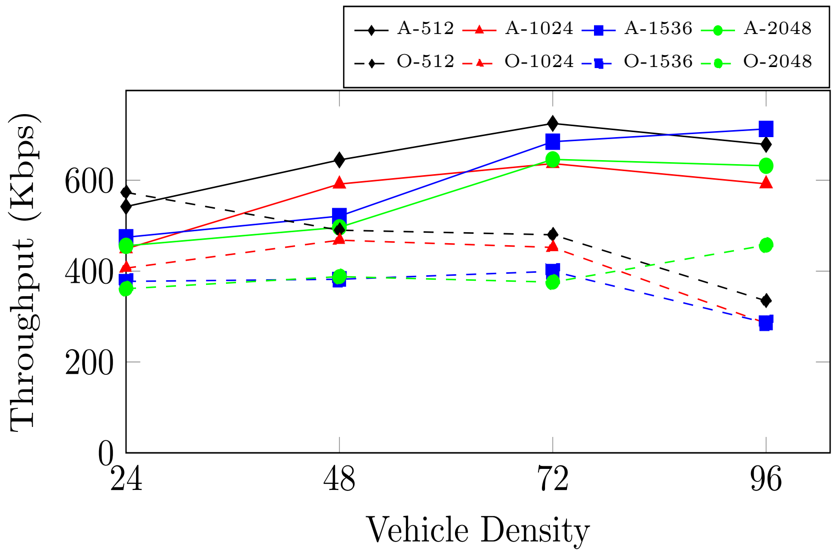


Figure. 3.16: Throughput for the city road network (500m)

overhead is keep on decreasing with data transmission rate as depicted in Figures 3.13 and 3.14. Intuitively, it can be observed that AODV protocol has more routing overhead at 250m transmission range, while it is lessen with 500m transmission range due to reduced number of route discovery messages.

Hence, intuitively, transmission range and road topology does affect the routing overhead. From the results, it can be concluded that data transmission rate, vehicle density and routing mechanism affect the routing overhead. Hence, protocols which maintain the route table have more routing overhead in VANET and makes it less applicable.

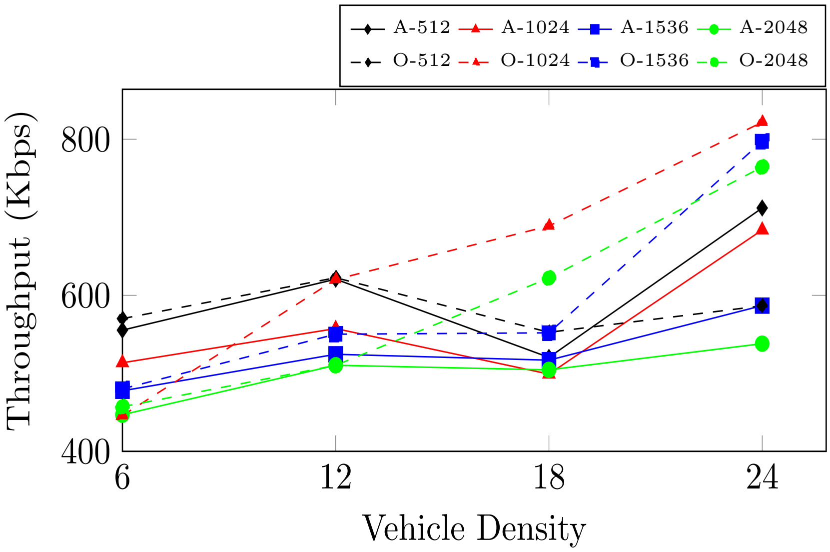


Figure. 3.17: Throughput for single crossroad network (250m)

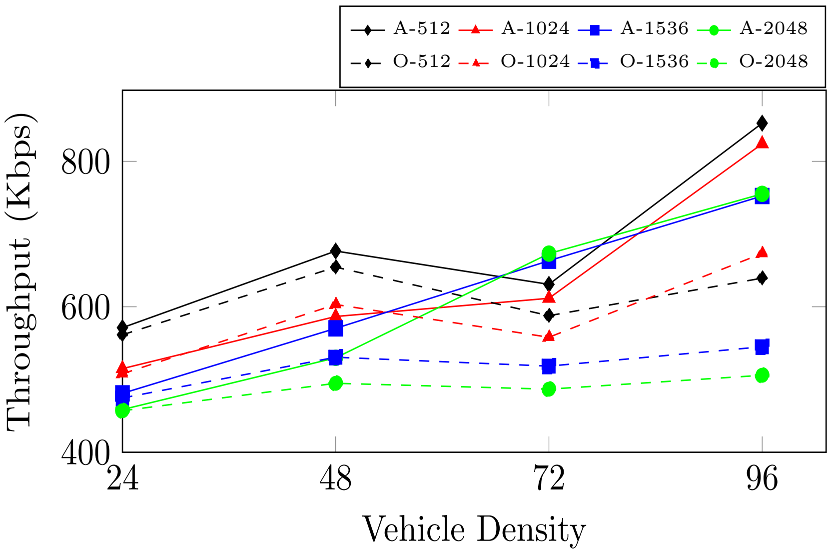


Figure. 3.18: Throughput for single crossroad network (500m)

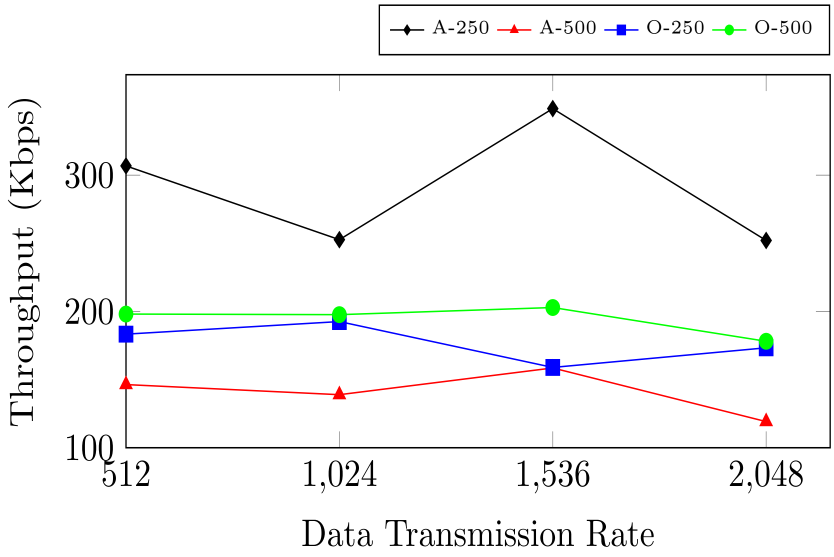


Figure. 3.19: Throughput with respect to data transmission rate for constant speed (city)

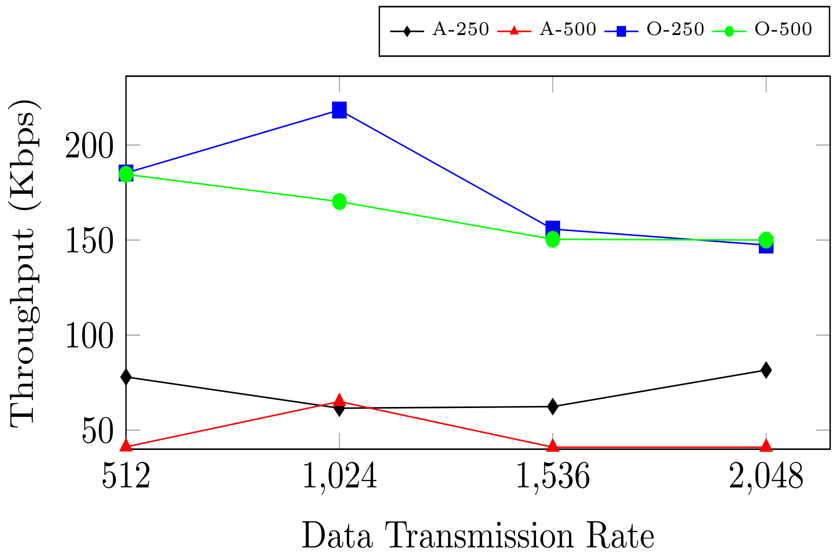


Figure. 3.20: Throughput with respect to data transmission rate for variable speed (city)

3.2.3 Throughput

The throughput of the network is the average number of bits transmitted per second. The throughput of the AODV protocol reaches to 750Kbps with entire

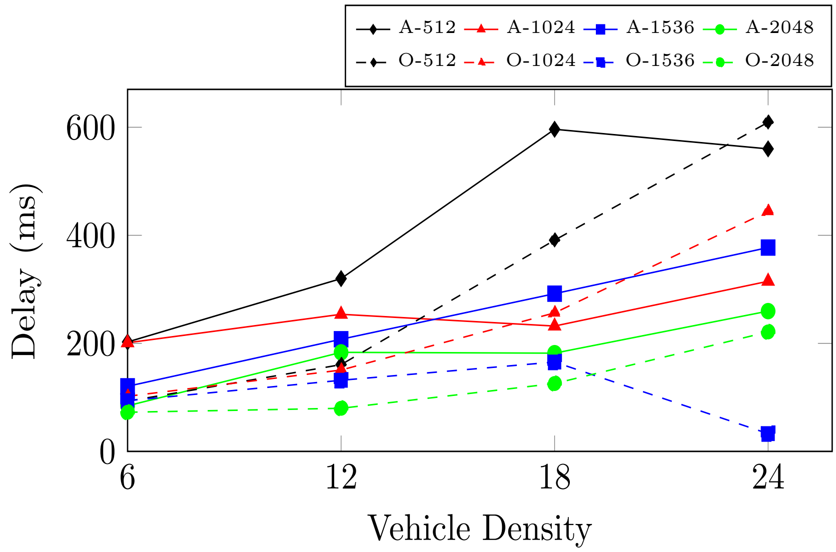


Figure. 3.21: Average delay for the city road network (250m)

city road network for 250m transmission range at 1024Kbps data transmission rate and it is the maximum throughput received among the AODV and OLSR protocols at all level of data transmission rate. The AODV protocol has stable throughput for the entire city road network at 512Kbps data transmission rate for both the transmission range. Both the protocols throughput decrease as the vehicle density increase as shown in Figures 3.15 and 3.16.

In case of single crossroad scenario, throughput increases as the vehicle density increases due to movement of the nodes near to each other as the nodes are deployed only on road segments and its intersection point rather than the city road network. However, OLSR protocol has more throughput compared to the AODV protocol in 250m transmission range and it increases as the vehicle density increases. Whereas, with respect to 500m transmission range, AODV protocol has a pretty stable throughput with increasing vehicle density. However, it decreases as the data transmission rate increases as shown in Figures 3.17 and 3.18.

With reference to data transmission rate, throughput of the AODV protocol at 250m transmission range is 350Kbps at 1536Kbps data transmission rate with constant speed, which is the highest throughput with respect to constant speed, due to less congestion. Similarly, with variable speed AODV protocol achieves

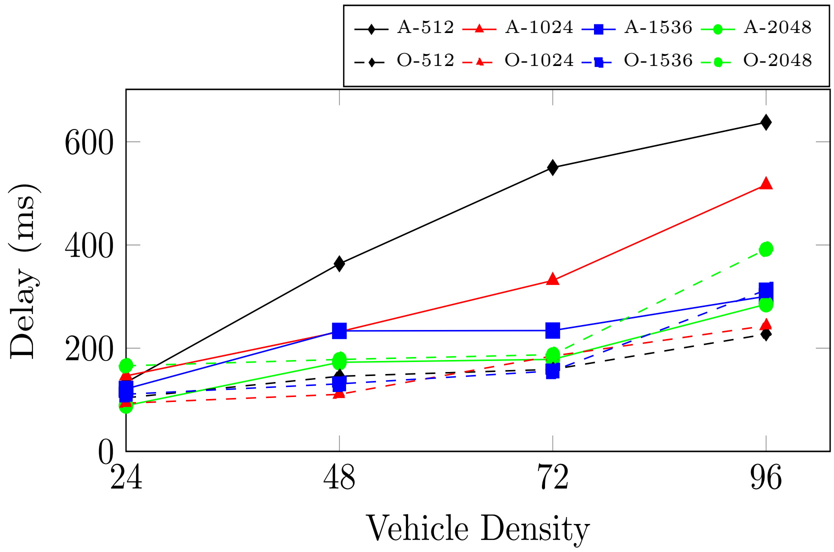


Figure. 3.22: Average delay for the city road network (500m)

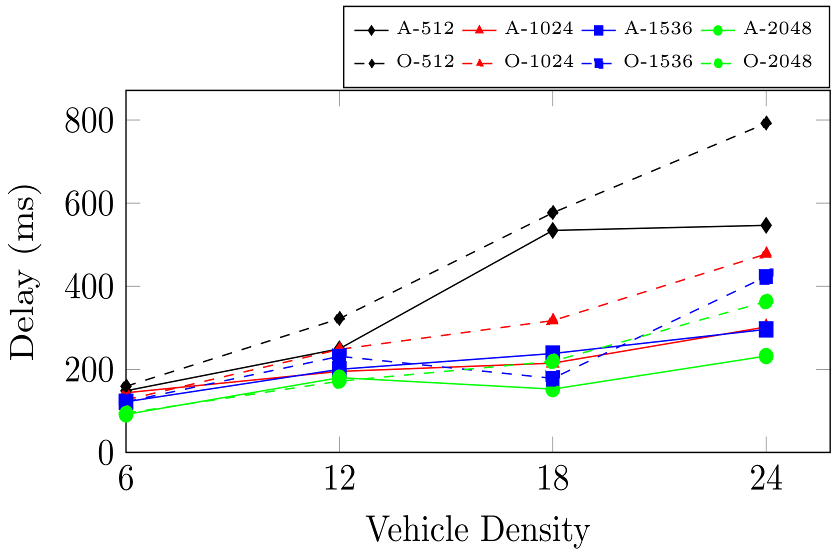


Figure. 3.23: Average delay for single crossroad network (250m)

220Kbps maximum throughput in 500m transmission range at 1024Kbps data transmission rate as shown in Figures 3.19 and 3.20. However, in both the cases OLSR could not achieve more than 190Kbps throughput.

Hence, throughput of the protocols decreases with respect to node density and data transmission rate for the city road network, due to more number of packets,

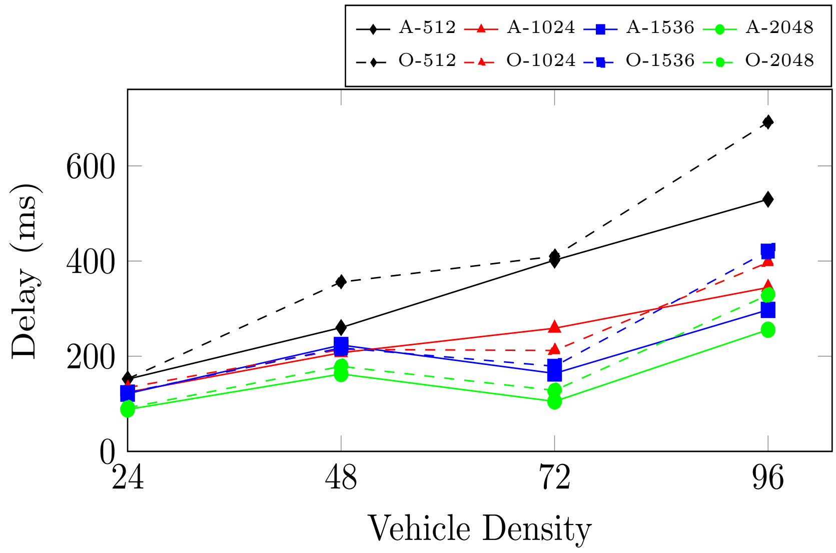


Figure. 3.24: Average delay for single crossroad network (500m)

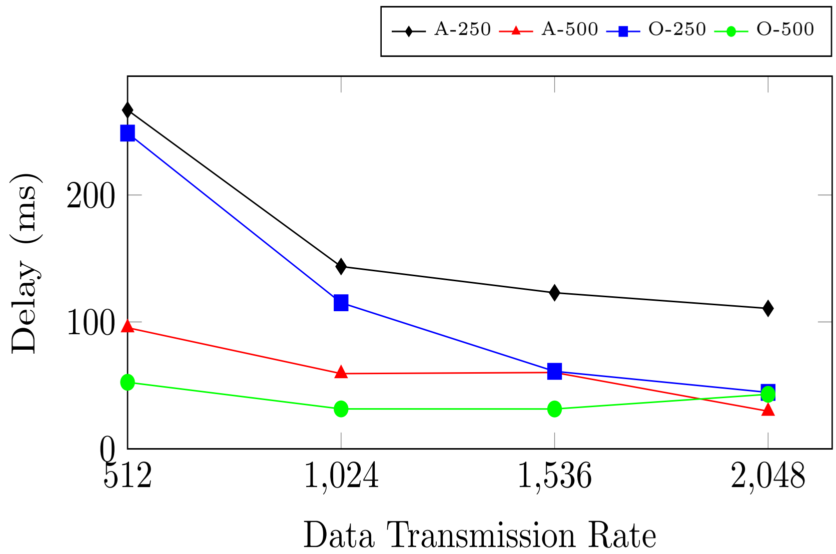


Figure. 3.25: Average delay with respect to data transmission rate for constant speed (city)

whereas it increases with single crossroad. Which makes it less applicable in VANET with respect to throughput. However, in some scenario throughput has been increased this may be due to the availability of the destination node for the longer time. It may happen that both the source and destination nodes might be

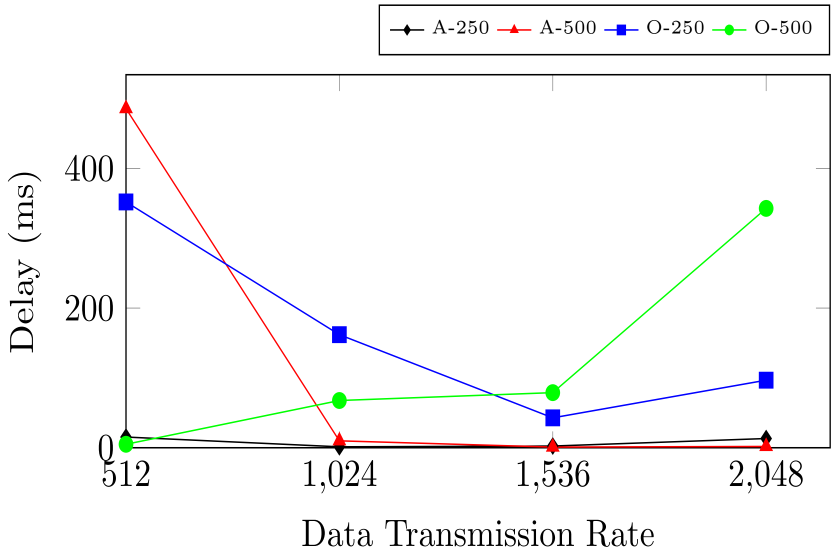


Figure. 3.26: Average delay with respect to data transmission rate for variable speed (city)

stable at traffic signal which is used in simulation.

3.2.4 Average Delay

Average delay is the measurement of end to end transmission delay between sender and receiver only for the correctly received packet. From Figures 3.21 and 3.22 it can be observed that AODV protocol has highest delay at 250m and 500m transmission range on 512Kbps data transmission rate for the entire city road network. Overall, the average delay decreases with the increase of data transmission rate for both the protocols as shown Figures 3.25 and 3.26. However, it is also observed that after 1536Kbps of data transmission rate, OLSR average delay increases as data transmission rate increases, which is an exception due to injection of more number of packets in network which get delayed due to route identification. Overall, from the results it is seen that average delay increases as the vehicle density increases with few exceptions. Nevertheless, OLSR protocol has less average delay compared to the AODV protocol as it maintains the route table.

With reference to single crossroad network, average delay is less, for the AODV protocol. However, OLSR protocol has similar delay compared to the entire city road network as shown in Figures 3.23 and 3.24. However, in all the scenarios AODV protocol has a more average delay compared to the OLSR protocol due to on-demand route discovery procedure. It is also observe that the transmission range and road topology have less effect on packet delay.

Hence, based on results both the protocols are less feasible to be used in VANET due to more average delay with respect to vehicle density.

3.3 SUMMARY

The AODV and OLSR protocols do not have stable PDR and throughput with respect to vehicle density and data generation rate. However, overall, routing overhead and average delay increases with vehicle density and decreases when data generation rate increases. It is also observed that the performance is better on single crossroad compared to multiple crossroad. Hence, performance computed considering single crossroad is not appropriate to decide the applicability of MANET routing protocols in VANET. In addition, performance with the constant speed is better than variable speed as it does not affect the topology compared to the real scenarios. Hence, based on obtained results for the entire city road network scenario, AODV and OLSR protocols are not feasible for VANET as endurance with vehicle density and data generation rate are not satisfactory with VANET characteristics.

Related Publication

- Raj K Jaiswal and Jaidhar C D **An Applicability of AODV and OLSR Protocols on IEEE 802.11p for City Road in VANET**, Internet of Things, Smart Spaces and Next Generation Networks and Systems, Volume 9247, **Lecture Notes in Computer Science**, Springer International Publishing, 2015, 286-298.

Chapter 4
Location Prediction Algorithm for a Nonlinear Vehicular Movement in VANET using Extended Kalman Filter

This chapter proposes the location prediction algorithm using EKF by considering nonlinear vehicular movement. The salient contributions of this chapter are:

- It proposes a location prediction algorithm using EKF.
- It considers nonlinear vehicular movement, particularly in the city.
- The efficacy of the proposed algorithm is evaluated on the real and model based traces for the city and highway scenarios.
- It compares the proposed algorithm performance with KF based location prediction.

The remaining sections of Chapter 4 are organized as follows: Section 4.1 explains about system model used in experiments. Section 4.2 briefs about KF and EKF. The location prediction algorithm is explained in Section 4.3. Section 4.4 and Section 4.5 discuss the implementation and evaluation settings and results of the prediction algorithm, respectively. The comparison of the proposed algorithm is shown in Section 4.6 and followed by summary in Section 4.7.

4.1 SYSTEM MODEL

All the vehicles are assumed to be equipped with an on-board unit and omnidirectional antenna. A vehicle communicates to another vehicle or RSU using IEEE 802.11p standard. It is also assumed that GPS and inertial navigation system are in place to measure the latitude, longitude, velocity and acceleration, orientation, steering angle, respectively. For the EKF, vehicle kinematics are defined considering Ackerman steering as shown in Figure 4.1, wherein Φ_1 and Φ_2 are the steering angles of the outer tire and inner tire, respectively. The orientation of the vehicle is determined by angle θ (Li et al. 2012). In this work, the steering angle is considered to be zero as the vehicle runs either in the city or on a highway. Thereon steering angles Φ_1 and Φ_2 get changed only at the turning point or during the lane change.

The state X of the vehicle at time t is defined by six parameters as $[x,\ y,\ v_x,\ v_y,\ a_x,\ a_y]$, where x and y represent the latitude and longitude of the vehicle. Whereas, v_x, v_y, a_x and a_y represent the x and y component of the velocity and acceleration, respectively.

The equation of motion of physics as in Equation (4.1), measures the changes in the state of the vehicle. In Equation (4.1), initial state of the vehicle is denoted by x_0 while v and a represent the velocity and acceleration of the vehicle, respectively. The time interval for the change in velocity is denoted by Δt.

$$x = x_0 + v.\Delta t + (a\Delta t^2)/2 \tag{4.1}$$

Hence, the state model X of the vehicle is defined as:

$$X = \begin{bmatrix} x \\ y \\ v_x \\ v_y \\ a_x \\ a_y \end{bmatrix} = \begin{bmatrix} x_0 + v_x\Delta t \\ y_0 + v_y\Delta t \\ v_{x0} + a_x\Delta t \\ v_{y0} + a_y\Delta t \\ a_{x0} + \dfrac{\Delta v_x}{\Delta t} \\ a_{y0} + \dfrac{\Delta v_y}{\Delta t} \end{bmatrix} \tag{4.2}$$

Here, $\dfrac{\Delta v_x}{\Delta t}$ and $\dfrac{\Delta v_y}{\Delta t}$ in (5.2) are the change in x and y components of the acceleration, respectively.

4.2 DESCRIPTION OF KF AND EKF

The process model of a system is designed to estimate the state of the system with a minimal set of information. Whereas, the measurement model describes the state of the system using measurement device. The process and measurement

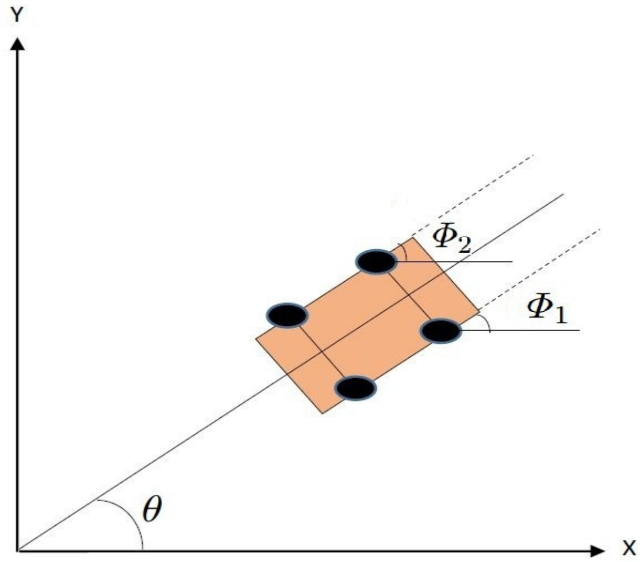


Figure. 4.1: Vehicle kinematics

model equations for a linear system used in KF for state estimation are defined in Equations (4.3) and (4.4) respectively.

$$\hat{x}_t^- = A\ \hat{x}_{t-1}^- + B\ u_{t-1} + w_{t-1} \tag{4.3}$$

$$z_t = H_t.\hat{x}_t^- + v_t \tag{4.4}$$

KF estimates and corrects a linear process recursively using feedback control mechanism. It estimates the state of the system in regular intervals to obtain the feedback measurement. The KF equations are grouped into Time Update and Measurement Update equations. The steps involved in state estimation of the system are described as follows:

Time Update (Prediction)

Location Prediction

$$\hat{x}_t^- = A\ \hat{x}_{t-1}^- + B\ u_{t-1} + w_{t-1} \tag{4.5}$$

Error Covariance

$$P_t^- = A\ P_{t-1}\ A^T + Q \tag{4.6}$$

Measurement Update (Correct)

Table 4.1: Description of KF symbols

Symbol	Description
A	State transition matrix.
A^T	Transpose of A.
B	Model matrix, steering angle- and acceleration change.
H_t	Measurement matrix at t.
H_t^T	Transpose of H_t.
I	Identity matrix.
K_t	Kalman gain at t.
P_t^-	Error covariance at t.
P_{t-1}	Error covariance at $t-1$.
P_t	Estimated error covariance by filter at t.
Q	Process noise covariance.
R	Measurement noise covariance.
u_{t-1}	Commanded input at $t-1$.
v_t	Measurement noise at t.
w_{t-1}	Process noise at $t-1$.
$\hat{x}_t^-$	location predicted at t.
$\hat{x}_{t-1}^-$	location at $t-1$.
$\hat{x}_t$	location predicted by filter at t.
z_t	Measured location at t.

Kalman Gain

$$K_t = P_t^- {H_t}^T (H_t P_t^- {H_t}^T + R)^{-1} \tag{4.7}$$

Prediction on Measurement z_t (Update)

$$\hat{x}_t = \hat{x}_t^- + K_t(z_t - H_t \hat{x}_t^-) \tag{4.8}$$

Error Covariance (Update)

$$P_t = (I - K_t H_t)\ P_t^- \tag{4.9}$$

In Equation (4.5), the state transition matrix A_t is obtained from the previous state $\hat{x}_{t-1}^-$. Whereas, $\hat{x}_t^-$ and P_t^- in Equations (4.5) and (4.6) are the prior (predicted) estimate of the state X and process error covariance respectively. The remaining description of each symbol used in KF is given in Table 4.1.

Kalman gain K_t in Equation (4.7) minimizes the error between predicted and measured values. Hence, K_t is the most critical factor in deciding the accuracy of the filter. The measured error covariance P_t is obtained using estimated error covariance matrix P_t^- and identity matrix I showed in Equation (5.1). $\hat{x}_t$ in Equation (4.8), is the estimated state of the system by KF. The estimated state $\hat{x}_t$ and error covariance P_t in correction steps are updated with $\hat{x}_t^-$ and P_t^- of prediction steps respectively for the computation of the next state (Welch & Bishop 1995).

4.2.1 Extended Kalman Filter

As discussed earlier, KF is designed to work with the linear system. It applies to a vehicular system in which the movement is linear, which is not practical in real world scenarios as explained in Section 2.6.

EKF is designed to work with the nonlinear system which can be used in location prediction algorithm in VANET. It is designed on the basis of KF for a nonlinear system. EKF linearized the nonlinear system using partial differentiation which yields the Jacobian matrix to be used in computation to estimate the current state of the system. The process and measurement models of the nonlinear system used with EKF are defined in Equations (4.10) and (4.11):

$$\hat{x}_t^- = f(\hat{x}_{t-1}^-, u_{t-1}, w_{t-1}) \tag{4.10}$$

$$z_t = h(\hat{x}_t^-, v_t) \tag{4.11}$$

The computational steps involved in EKF for location prediction in VANET are explained as:

Time Update (Prediction)

Location Prediction

$$\hat{x}_t^- = f(\hat{x}_{t-1}^-, u_{t-1}, w_{t-1}) \tag{4.12}$$

Error Covariance

$$P_t^- = F_t\ P_{t-1}F_t^T + W_t Q {W_t}^T \tag{4.13}$$

Measurement Update (Correct)

Kalman Gain

$$K_t = P_t^- {H_t}^T (H_t P_t^- {H_t}^T + V_t R {V_t}^T)^{-1} \tag{4.14}$$

Prediction on Measurement z_t (Update)

$$\hat{x}_t = \hat{x}_t^- + K_t\big(z_t - h(\hat{x}_t^-, v_t)\big) \tag{4.15}$$

Error Covariance (Update)

$$P_t = (I - K_t H_t)\ P_t^- \tag{4.16}$$

As EKF is an extended form of KF, thus, most of the terms are similar to KF as explained in Section 4.2 except F_t, W_t, H_t and V_t in Equations (4.13) and (4.14), respectively which are the Jacobian matrix defined as:

$$F_t = \frac{\partial f(\hat{x}_{t-1}^-, 0, 0)}{\partial x} \tag{4.17}$$

$$W_t = \frac{\partial f(\hat{x}_{t-1}^-, 0, 0)}{\partial w} \tag{4.18}$$

$$H_t = \frac{\partial h(\hat{x}_{t-1}^-, v_t)}{\partial x} \tag{4.19}$$

$$V_t = \frac{\partial h(\hat{x}_{t-1}^-, 0, 0)}{\partial v} \tag{4.20}$$

Whereas, F_t^T, ${H_t}^T$, ${V_t}^T$ and ${W_t}^T$ are the transpose of F_t, W_t, H_t and V_t. Jacobian matrix F_t is computed on partial differentiation of $f(\hat{x}_{t-1}^-, u_{t-1}, w_{t-1})$ with respect to $\hat{x}_{t-1}^-$ as shown in Equation (4.21).

$$\frac{\partial f}{\partial x} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & . & .. & ... & \frac{\partial f_1}{\partial x_6} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & . & .. & ... & \frac{\partial f_2}{\partial x_6} \\ . & .. & .. & .. & .. & .. \\ . & .. & .. & .. & .. & .. \\ . & .. & .. & .. & .. & .. \\ \frac{\partial f_6}{\partial x_1} & \frac{\partial f_6}{\partial x_2} & . & .. & ... & \frac{\partial f_6}{\partial x_6} \end{bmatrix} \tag{4.21}$$

Where $x = \hat{x}_{t-1}^-$, Similarly, Jacobian matrix of W_t, H_t and V_t are obtained on partial differentiation of $f(\hat{x}_{t-1}^-, u_{t-1}, w_{t-1})$ with respect to w_t and $h(\hat{x}_t^-, v_t)$ with respect to $\hat{x}_{t-1}^{-}$ and v_t respectively.

In this model, control input u_{t-1} and process noise w_{t-1} are assumed to be zero. Hence, process model in Equation (4.12) becomes $f(\hat{x}_{t-1}^{-}, 0, 0)$ whereas measurement model $h(\hat{x}_t^{-}, v_t)$ remains the same.

4.3 LOCATION PREDICTION ALGORITHM

To predict the location of a vehicle in VANET considering nonlinear movement, EKF is used in the prediction algorithm as mentioned in Figure 4.2. It is implemented in the system model as described in Section 4.1. To initialize the filter, F_t, W_t, H_t, V_t, P_t, Q and R parameters are initialized as follows:

Jacobian matrix F_t is obtained on differentiating partially to the function $f(\hat{x}_{t-1}^{-}, 0, 0)$ with respect to $\hat{x}_{t-1}^{-}$ which is state vector measured at time $t-1$. Δt is the sampling interval and assumed to be one. The initial value of F_t is defined as:

$$F_t = \begin{bmatrix} 1 & 0 & \Delta t & 0 & 0 & 0 \\ 0 & 1 & 0 & \Delta t & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.22}$$

The initial value of Jacobian matrix W_t is obtained on a partial differentiation of function $f(\hat{x}_{t-1}^{-}, 0, 0)$ with respect to w_{t-1} since the process noise w_{t-1} is assumed to be zero. Hence, the initial value of W_t is defined as:

$$W_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4.23}$$

Similarly, the initial value of Jacobian matrix H_t and V_t are obtained on differentiating partially to $h(\hat{x}_t^{-}, v_t)$ with respect to $\hat{x}_t^{-}$ and v_t as mentioned in matrices

(5.10) and (5.11) as:

$$H_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.24}$$

and

$$V_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.25}$$

The error covariance matrix P_t is obtained using matrix (4.26) in which non-diagonal elements represent the correlation term which is assumed to be independent and does not affect the matrix value. The diagonal elements of the matrix correspond to the covariance in the states.

$$P_t = \begin{bmatrix} e(x,x) & e(x,y) & e(x,v_x) & e(x,v_y) & e(x,a_x) & e(x,a_y) \\ e(y,x) & e(y,y) & e(y,v_x) & e(y,v_y) & e(y,a_x) & e(y,a_y) \\ e(v_x,x) & e(v_x,y) & e(v_x,v_x) & e(v_x,v_y) & e(v_x,a_x) & e(v_x,a_y) \\ e(v_y,x) & e(v_y,y) & e(v_y,v_x) & e(v_y,v_y) & e(v_y,a_x) & e(v_y,a_y) \\ e(a_x,x) & e(a_x,y) & e(a_x,v_x) & e(a_x,v_y) & e(a_x,a_x) & e(a_x,a_y) \\ e(a_y,x) & e(a_y,y) & e(a_y,v_x) & e(a_y,v_y) & e(a_y,a_x) & e(a_y,a_y) \end{bmatrix} \tag{4.26}$$

The initial state estimation of X is fixed at $\hat{x}_0 = 0$ and initial error covariance P_0 is fixed at a large value to minimize the error gap. Thus, the initial error covariance matrix P_0 is defined as:

$$P_0 = \begin{bmatrix} 1000 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1000 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1000 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1000 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1000 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1000 \end{bmatrix} \tag{4.27}$$

In the literature reviews, various methods have been proposed to select the appropriate values of Q and R. However, in this study Q and R values are taken manually in an ad hoc manner (Bavdekar et al. 2011). The measurement noise

R is the device error and defined by the manufacturer. Hence, the measurement noise R is defined as in (4.28) where R_x and R_y are the change in latitude and longitude respectively.

$$R = \begin{bmatrix} R_x & 0 \\ 0 & R_y \end{bmatrix} \tag{4.28}$$

The initial value of measurement noise R is:

$$R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{4.29}$$

The process noise Q is the observed error in the computational process which is difficult to measure. Thus, the initial value of Q is kept minimum to make the process error free. The initial value of Q is defined as:

$$Q = \begin{bmatrix} 0.01 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.01 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.01 \end{bmatrix} \tag{4.30}$$

The value of Q and R can be changed to tune the filter to get the best estimation of the vehicle state.

4.4 IMPLEMENTATION AND EVALUATION SETTINGS

The prediction algorithm using EKF as shown in Figure 4.2 and KF are implemented in C language on Intel Core i7-3770 CPU @ 3.40GHz on Windows 7 machine rather then network simulator. Both EKF and KF filters iterate the state estimation process for 25 times to reduce the error to get the best state estimation.

4.4.1 GPS Traces/Dataset

The dataset used in our experiments is classified into the real and model based dataset. Further, these mobility traces are categorized into the city and highway scenarios, as the city road layouts are different compared to the highway. In addition, the speed of the vehicle on the highway used to be consistent for a long time, unlike the city.

- *Real GPS Traces* for the city and highway scenarios are retrieved from the OpenStreetMap. Flen city from Sweden is considered in the experiments. As retrieved, traces are just similar to the city like road structure. For the highway scenario, traces are retrieved haphazardly from OpenStreetMap which describes the road structure almost the same as the highway. In both the traces speed changes based on the vehicle movement.

- *Model Based Traces* are obtained for the city and highway scenarios using VANETMOBISIM simulator (Härri et al. 2006). The intelligent driving model is chosen as it supports for the acceleration/deceleration, driver behavior, traffic signal and politeness factor which make the vehicular mobility traces equal to the real-time vehicular traffic. For the highway scenario, simulation is conducted for a short time to get the traces equal to the highway scenario. Due to the lack of support of the simulator for the highway. The parameters considered for trace generation for the city and highway scenarios are mentioned in Table 4.2. However, junction points and traffic lights are not considered in the highway scenario.

4.4.2 Parameters for Performance Measurement

The efficiency of the prediction algorithm is measured on RMSE, DE, AEDE and VE. These parameters are more appropriate to measure the performance of a prediction algorithm.

4.4.2.1 Root Mean Square Error (RMSE)

It computes the error between measured and predicted location.

The RMSE for a prediction algorithm with respect to the measured value is defined as the square root of the mean squared error. Equation (4.31) calculates the RMSE of the prediction algorithm (Chai & Draxler 2014).

$$\text{RMSE} = \sqrt{1/N \sum_{t=1}^{N} (x_t - \hat{x}_t)^2} \tag{4.31}$$

Where x_t and $\hat{x}_t$ are the measured and predicted location of the vehicle respectively. N is the total number of the predictions made.

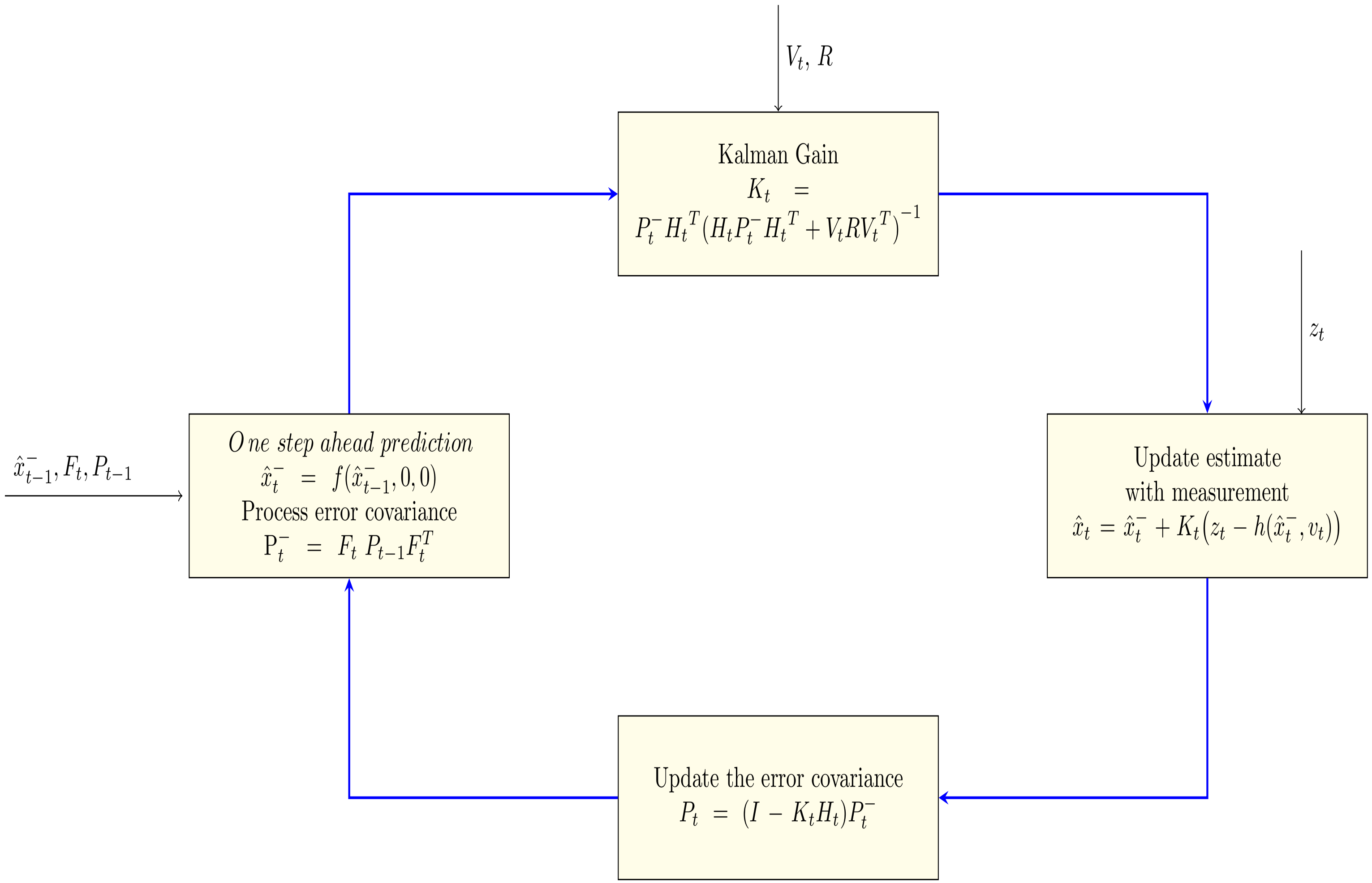


Figure. 4.2: Prediction algorithm using EKF

Table 4.2: Parameters for model based trace (Jaiswal & Jaidhar 2015)

Description	**Values**
Simulator	VANETMOBISIM
X dim.(m)	1000
Y dim.(m)	1000
No.of Traffic lights	05
Traffic Light Duration (s)	60
No. of Lanes	2
Min. Speed (m/s)	0.5
Max. Speed (m/s)	35
Politeness Factor	0.2,0.5,0.8
Maximum Acceleration	$0.9(m/s^2)$
Maximum Deceleration	$0.6(m/s^2)$
Min. Congestion Distance	2m
Safe Headway Time (s)	2
Length of Vehicle	5m

4.4.2.2 Distance Error (DE)

It measures the distance gap between measured and predicted location. It is computed using Euclidean distance as:

$$\mathrm{d}_{error} = \sqrt{(x_t - \hat{x}_t)^2 + (y_t - \hat{y}_t)^2} \tag{4.32}$$

x_t, y_t and $\hat{x}_t$, $\hat{y}_t$ in Equation (4.32), are the measured and predicted location of the vehicle respectively.

4.4.2.3 Average Euclidean Distance Error (AEDE)

AEDE measures the average distance error between measured and predicted location using Euclidean distance. Equation (4.33) used to calculate the AEDE for each scenario is explained as:

$$\mathrm{AEDE} = 1/N \sum_{i=1}^{N} \sqrt{(x_t - \hat{x}_t)^2 + (y_t - \hat{y}_t)^2} \tag{4.33}$$

4.4.2.4 Velocity Error (VE)

It measures the difference between measured and predicted velocity of the vehicle as follows:

$$\text{VE} = |V_m - V_p| \tag{4.34}$$

In Equation (4.34), V_m and V_p are the measured and predicted velocity, respectively.

4.5 RESULTS AND DISCUSSION

The EKF based prediction results are computed for each scenario viz. real and model based traces as discussed in Subsection 4.5.1 and compared with KF in Section 4.6. For each sub-category of model based trace as discussed in Subsection 4.4.1, it is observed that the traces generated from the VANETMOBISIM do not resemble the real GPS coordinates in any form such as angle or universal transverse mercator. The former one uses two dimensional Cartesian coordinate system to depict the location of an object on Earth's surface. The coordinates of the location on Earth's surface measured by the GPS system varies between -180 to 180 with respect to the latitude and longitude. However, trace generated from VANETMOBISIM takes the coordinates based on defined simulation area. For instance, if the simulation area is 1000x1000 m^2 then, the coordinates point varies between 0 to 1000. Based on these observations, the measurement unit for the location accuracy in meter, distance error in the meter and velocity error in Km/h are inappropriate for the traces generated from the VANETMOBISIM. Hence, the results are measured in decimal points rather than their actual measurement units.

4.5.1 Location Prediction with Extended Kalman Filter

4.5.1.1 Location Prediction Based on Model Traces

Figures 4.3 and 4.4 use magnifier to enhance the visibility of the results. Fig. 4.3 shows the prediction of the vehicle location in model based city. Intuitively, it is evident that location prediction is almost equal to the measured location with a few exceptions at some points. Though the results are in favour of EKF, however, similar location precision is difficult to get in real time scenario as the

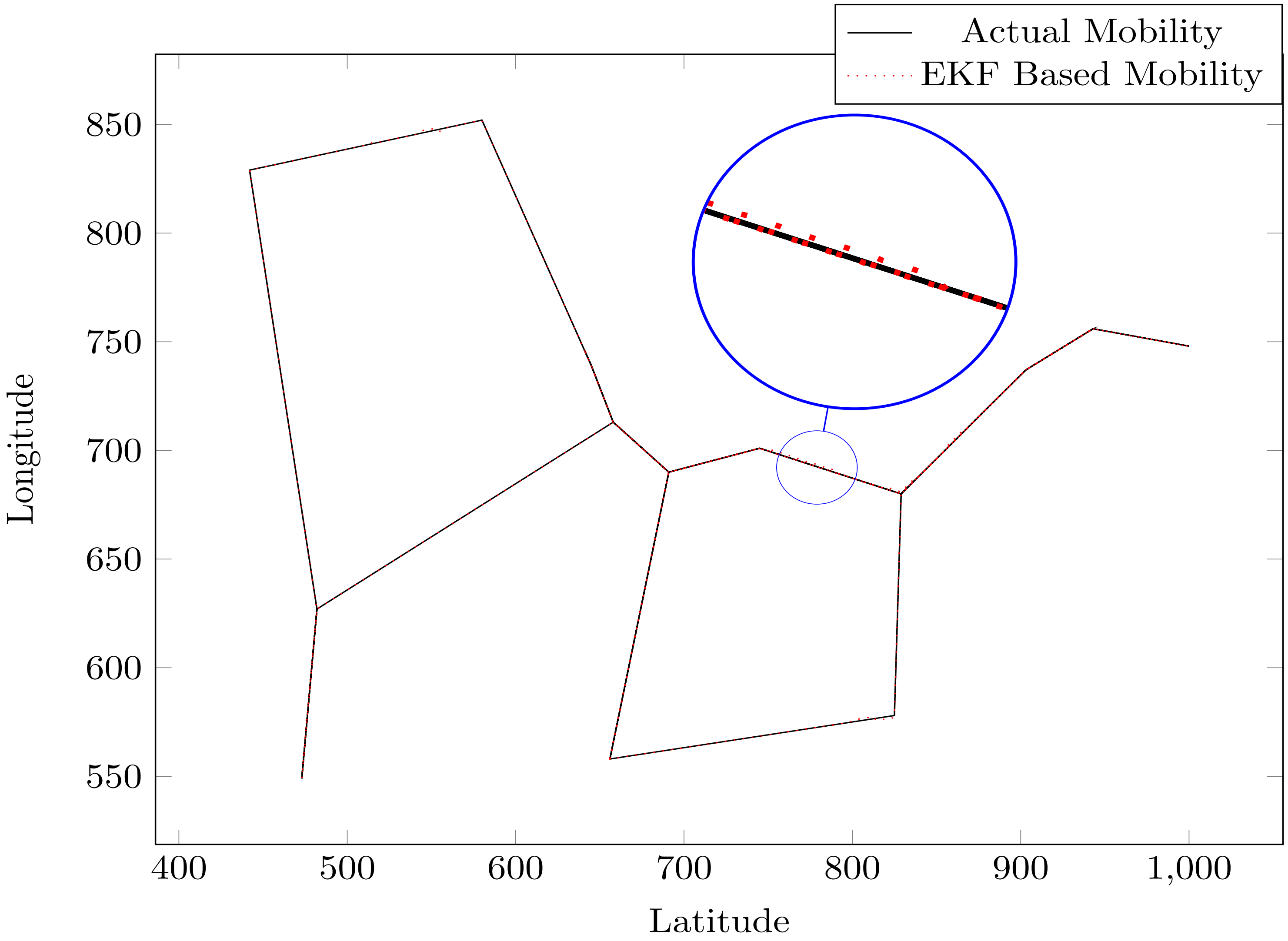


Figure. 4.3: Vehicle mobility prediction for the city scenario based on model trace using EKF.

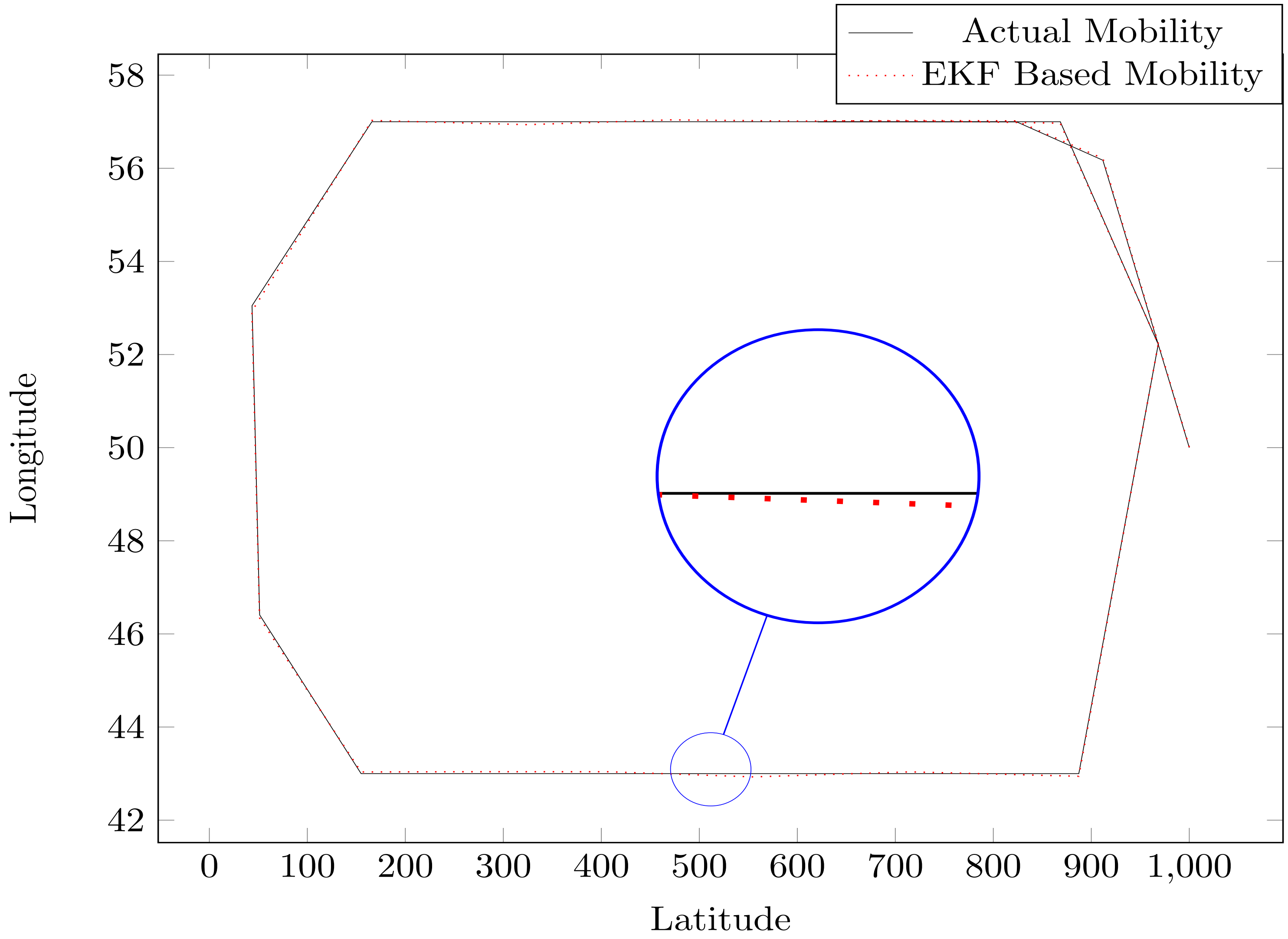


Figure. 4.4: Vehicle mobility prediction for the highway scenario based on model trace using EKF.

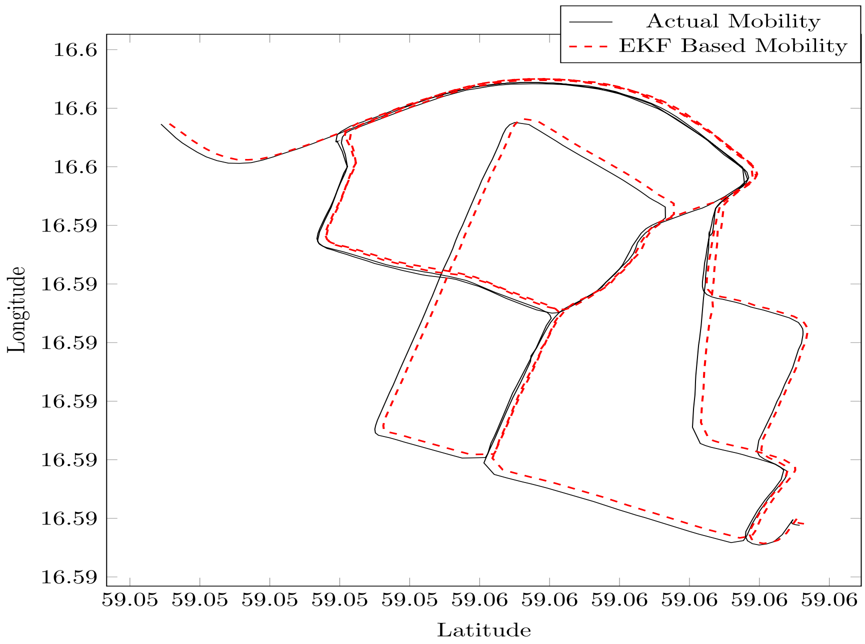


Figure. 4.5: Vehicle mobility prediction for the city scenario based on real trace using EKF.

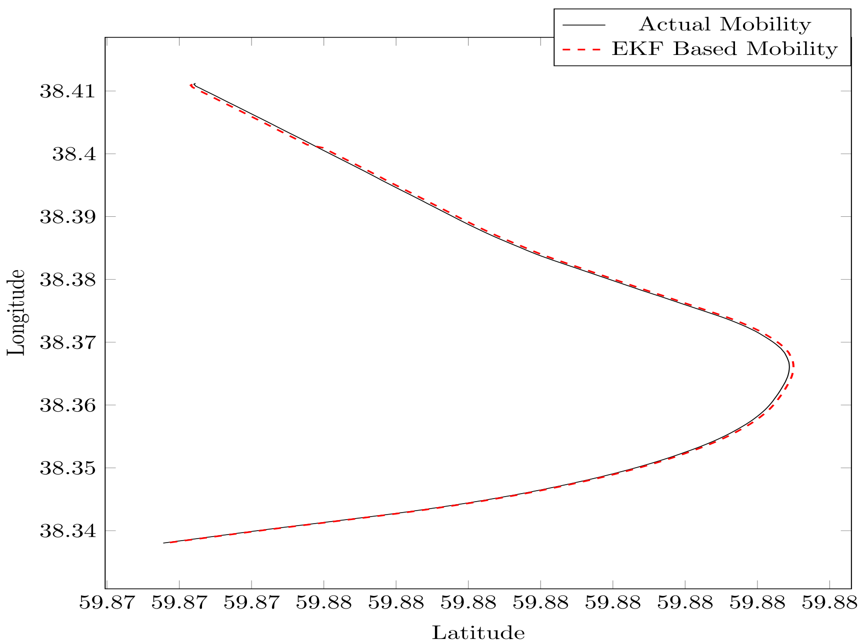


Figure. 4.6: Vehicle mobility prediction for the highway scenario based on real trace using EKF.

difference between two locations is huge as compared to real traces. In real traces, location changes up to 10 decimal points which is more evident while comparing the latitude and longitude coordinates in Figure 4.3, Figure 4.4 with Figure 4.5 and Figure 4.6, respectively. The prediction algorithm performance is slightly less on the highway scenario as compared to the city scenario. However, both the performances are in favour of EKF as location prediction is close to the measured location.

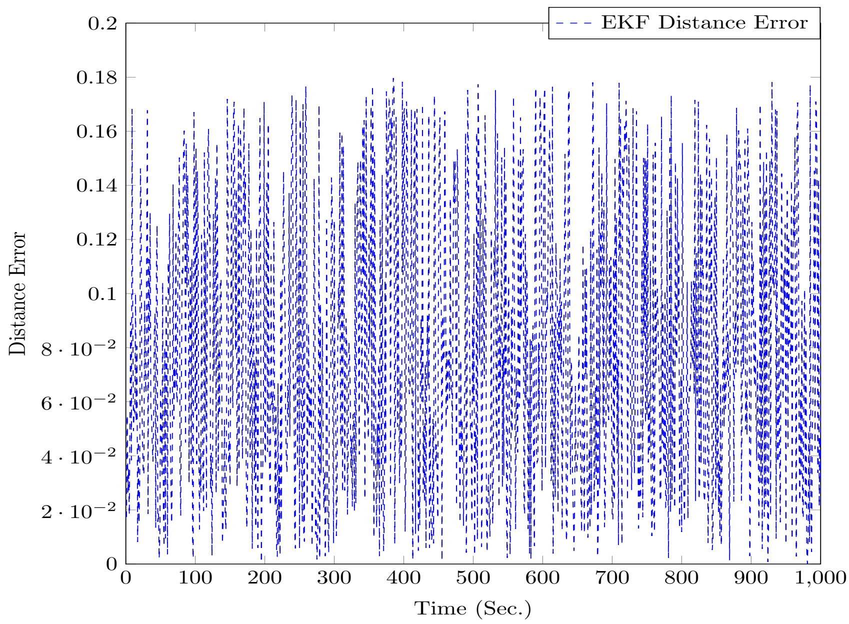


Figure. 4.7: Distance Error (DE) in the city scenario based on model trace (EKF).

4.5.1.2 Location Prediction Based on Real Traces

The accuracy of location prediction with real GPS traces for the city and highway scenarios are less compared to the model based traces as shown in Figures 4.5 and 4.6. However, predicted location with the real traces is close to the measured location as the difference between these two locations is changed up to eight decimal points. This difference is taken as the benchmark to decide the accuracy of prediction. Hence, based on these observations EKF based prediction is an appropriate technique to be used with those applications which demand the highest accuracy in location prediction such as cooperative driving and collision warning

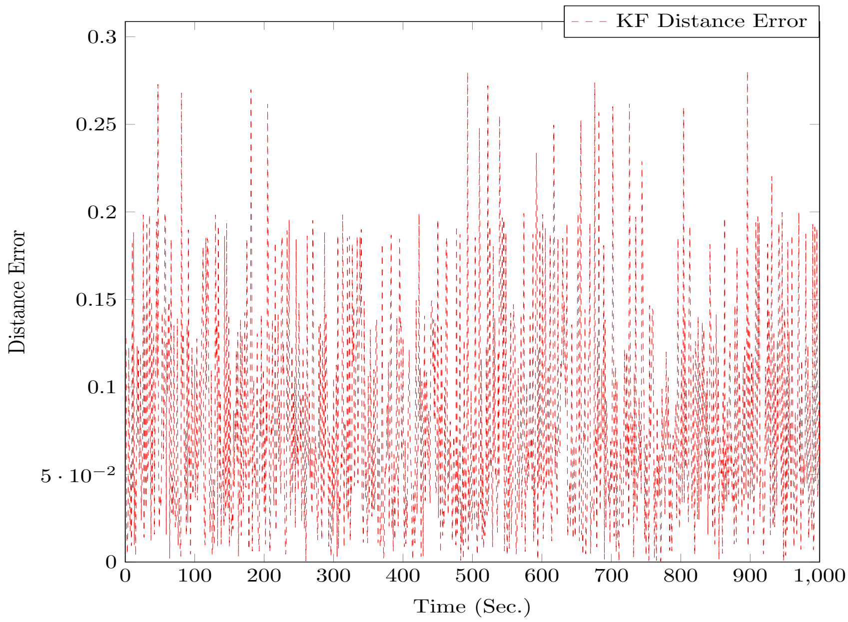


Figure. 4.8: Distance Error (DE) in the city scenario based on model trace (KF).

system. Hence, accuracy in location prediction with real GPS traces is practical and acceptable with EKF whereas EKF based location prediction with model based traces is not feasible in real world scenarios as it coordinates system.

4.6 PERFORMANCE COMPARISON WITH KF BASED PREDICTION

The performance of the proposed EKF based prediction is compared with the KF based prediction on DE, RMSE, AEDE and VE parameters. For both the filters, the process model, measurement model and computational steps are same as explained in Section 4.2.

4.6.1 DE Based Comparison

The following subsections compare the DE between EKF and KF based prediction.

4.6.1.1 DE with Model Trace

From, Figures 4.7 and 4.9, it is observed that EKF has 0.175 and 0.10 maximum DE in the city and highway respectively. However, 0 and 0.01 are the minimum DE with respect to the city and highway. Hence, on the highway distance error is less compared to the city using EKF based prediction. With reference to KF based prediction, it is noticed that 0.27 and 0.177 are the maximum DE in the city and highway scenarios as shown in Figures 4.8 and 4.9. Overall, EKF has less DE compared to KF in both the scenarios.

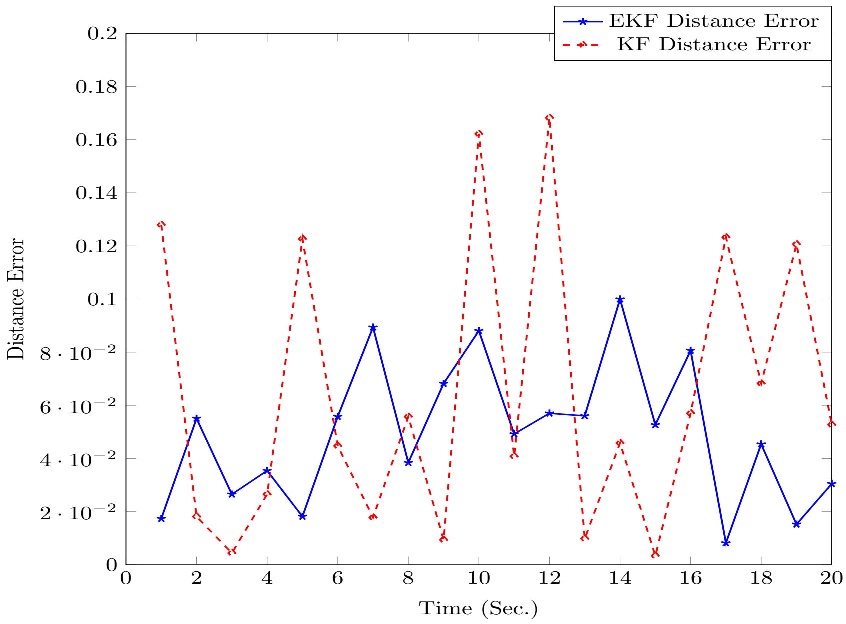


Figure. 4.9: Distance Error (DE) in the highway scenario based on model trace (EKF/KF).

4.6.1.2 DE with Real Trace

Based on the results, as shown in Figures 4.12 and 5.28, it is found that the EKF has the maximum DE of 0.18 and 0.125 for the city and highway scenarios, respectively. However, DE increased to 0.24 and 0.179 using KF based prediction in the city and highway as shown in Figures 4.11 and 4.12, respectively. KF based prediction has more DE compared to the EKF with real trace.

Intuitively, DE is less for the highway as compared to the city with both models using EKF and KF. However, DE slightly increased in KF based prediction in all the scenarios.

Note: Some of the figures are drawn separately for EKF and KF due to superimposition of the images.

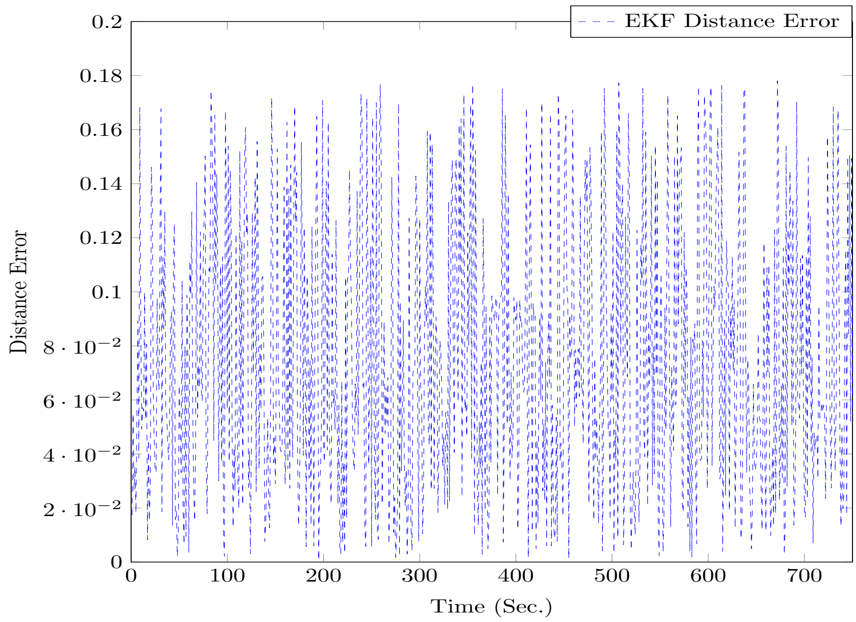


Figure. 4.10: Distance Error (DE) in the city scenario based on real trace (EKF).

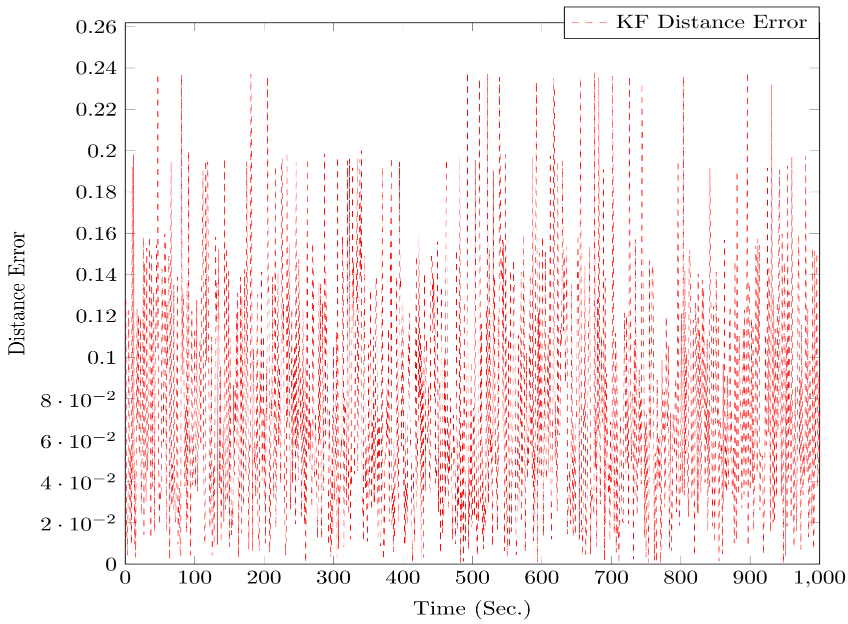


Figure. 4.11: Distance Error (DE) in the city scenario based on real trace (KF).

4.6.2 VE Based Comparison

The following subsections compare the VE between EKF and KF based prediction.

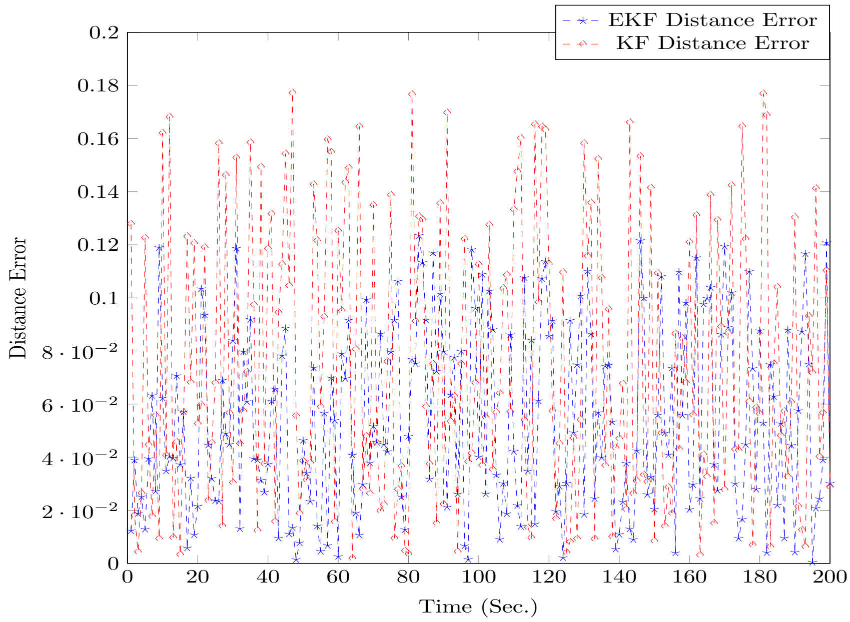


Figure. 4.12: Distance Error (DE) in the highway scenario based on real trace (EKF/KF).

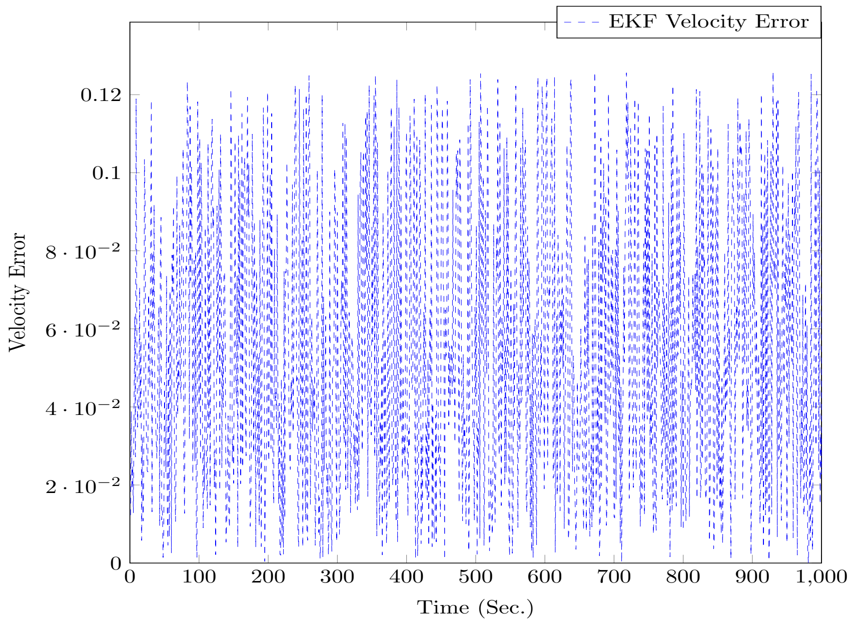


Figure. 4.13: Velocity error in the city scenario based on model trace (EKF).

4.6.2.1 VE with Model Trace

From Figures 4.13 and 4.15, it is learned that EKF has maximum VE of 0.125 and 0.10 in the city and highway scenarios respectively. However, VE increased to

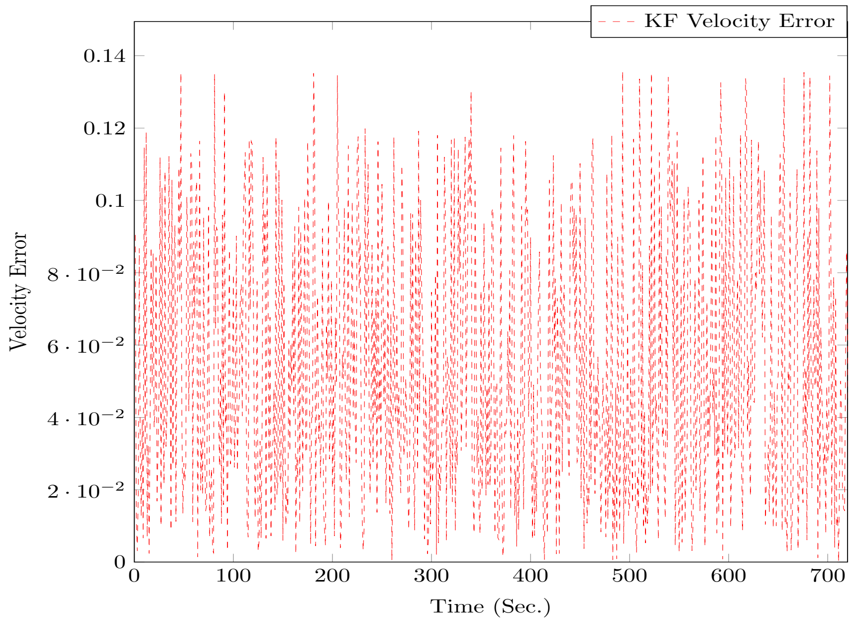


Figure. 4.14: Velocity error in the city scenario based on model trace (KF).

0.138 and 0.196 in the city and highway scenario using KF as shown in Figures 4.14 and 4.15, respectively. In general, EKF has less VE compared to KF in all the scenarios. However, KF has more VE on the highway compared to the city, unlike EKF.

4.6.2.2 VE with Real Trace

The maximum VE noted for EKF is 0.127 and 0.122 for the city and highway respectively as shown in Figures 4.16 and 4.18. VE increases marginally to 0.143 and 0.131 in the city and highway using KF as shown in Figures 4.17 and 4.18, respectively. In both the cases viz. EKF and KF highway has less VE compared to the city. However, EKF outperforms KF with a marginal difference in all the scenarios.

In general, KF has more VE compared to EKF in all the scenarios.

4.6.3 RMSE Based Comparison

In Figure 4.19, Figures 4.20 and 4.21, R and M on the x-axis are used for real and model based traces which are used in conjunction with the city and highway.

From the Figure 4.19, it is observed that the KF based prediction has highest

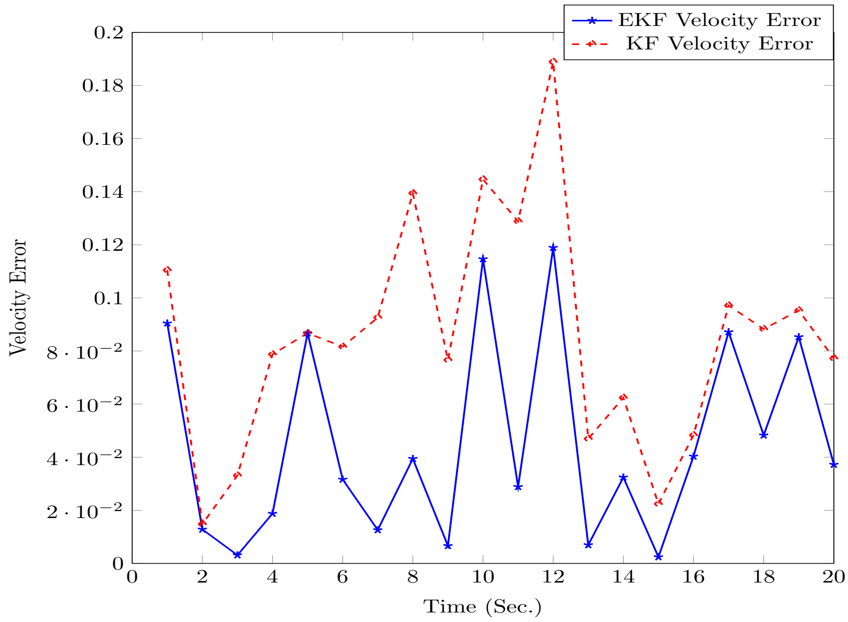


Figure. 4.15: Velocity error in the highway scenario based on model trace (EKF/KF).

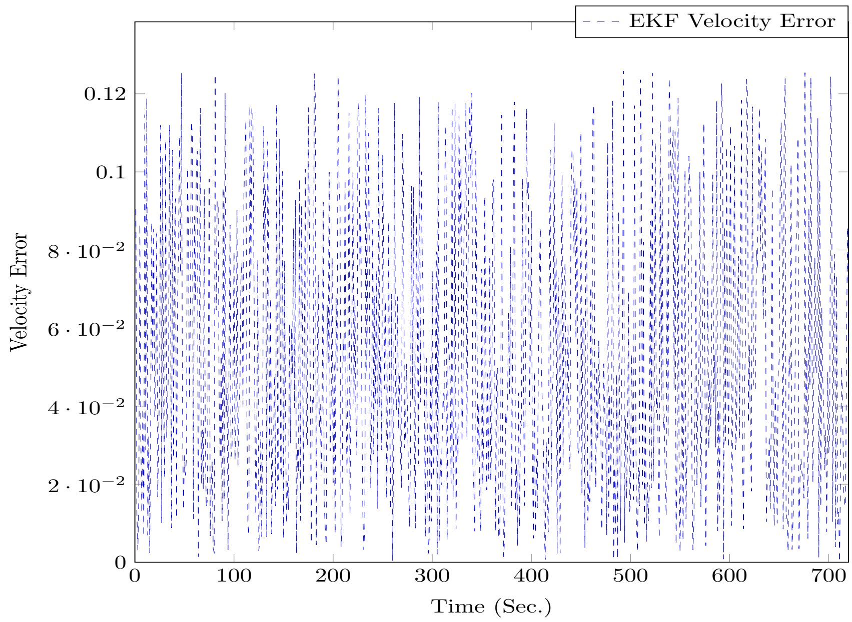


Figure. 4.16: Velocity error in the city scenario based on real trace (EKF).

0.062 error in latitude whereas with EKF based prediction it reduced to 0.042. Figure 4.20 shows the error in longitude. Intuitively, it can be seen in the result that the error is most likely to be similar to an observed error for the latitude.

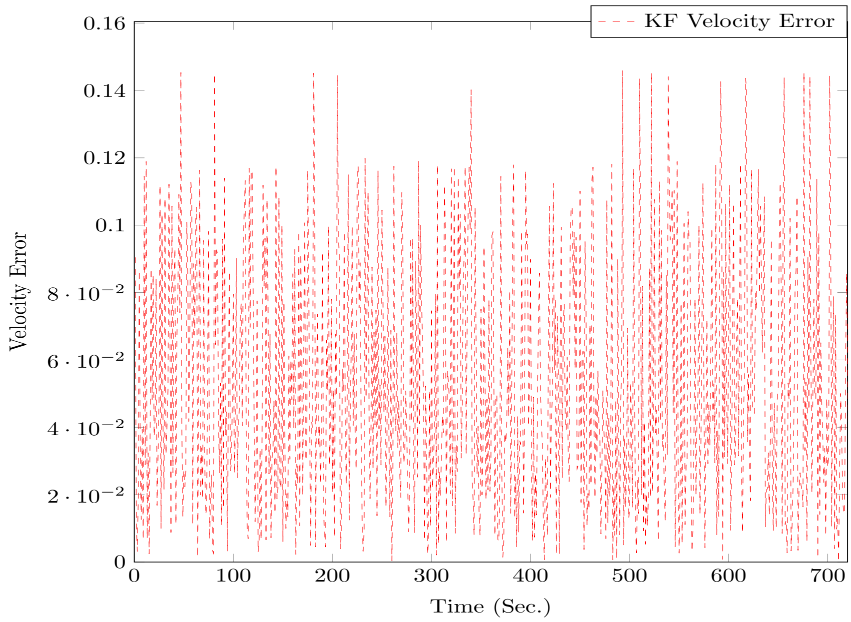


Figure. 4.17: Velocity error in the city scenario based on real trace (KF).

However, it has an exception with EKF based prediction on model based city traces wherein the error reduced to 0.022.

Based on RMSE results for the latitude and longitude as shown in Figures 4.19 and 4.20, it is evident that the EKF based prediction has less error in the predicted location compared to the KF based prediction.

4.6.4 AEDE Based Comparison

The AEDE is shown in Figure 4.21 for all the scenarios. It is as highest as 0.14 for KF based prediction with real traces for the highway scenario whereas with the EKF based prediction AEDE is reduced to 0.122. From the figure, it is observed that KF and EKF have highest AEDE with real traces for highway and model based traces for the city, respectively, which is seen as an exception. Overall, EKF has less AEDE compared to the KF in all the scenarios.

4.6.5 Analysis of Time Complexity

The time complexity of the KF based prediction algorithm is $O(n^3)$ where n represents the number of parameters used in the state as discussed in (Feng et al. 2015). As it involves the matrix multiplication and inverse operation. However,

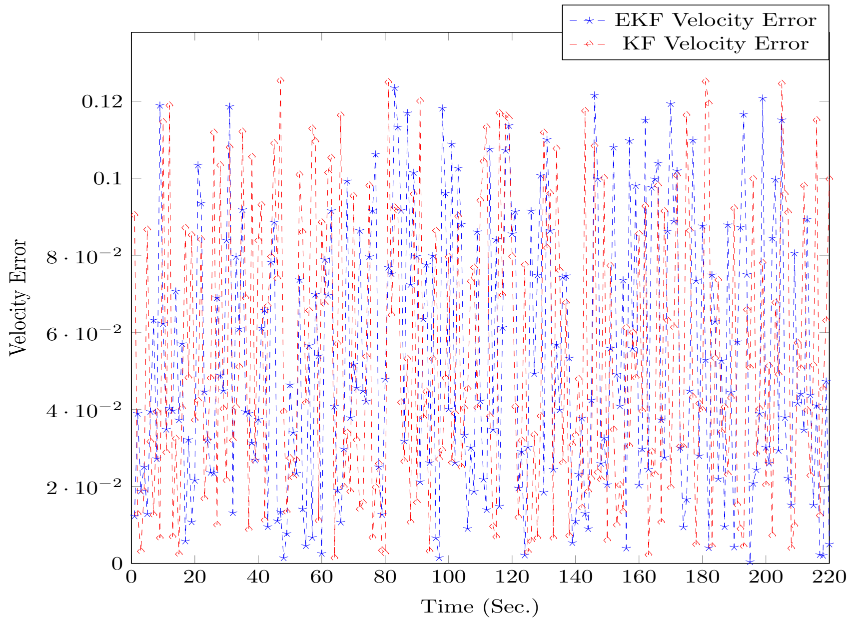


Figure. 4.18: Velocity error in the highway scenario based on real trace (EKF/KF).

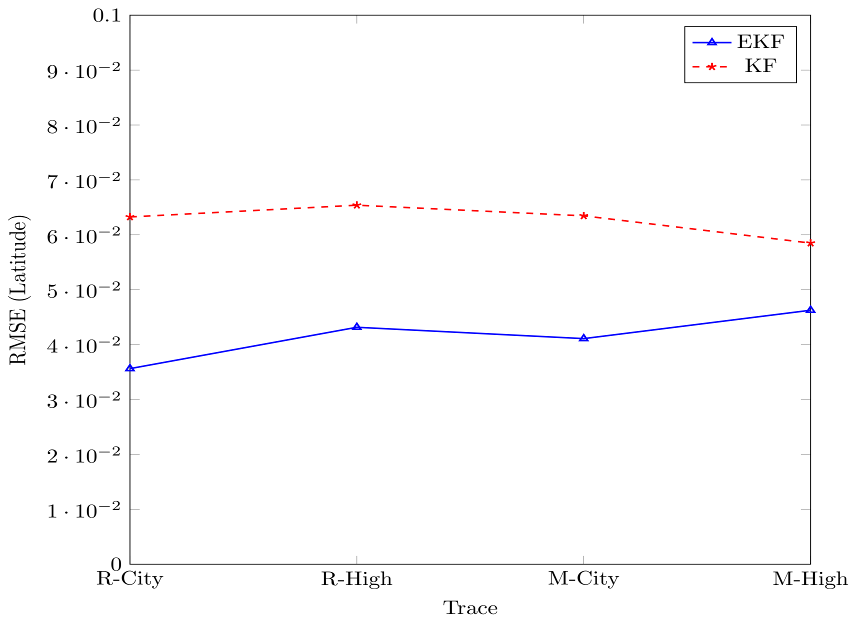


Figure. 4.19: Root Mean Square Error (RMSE) for latitude.

the time complexity for EKF based prediction algorithm is seen as a future work as it involves the computation of nonlinear function in Equations (4.12) to (4.15) and partial differentiation to compute the Jacobian matrix in addition to matrix

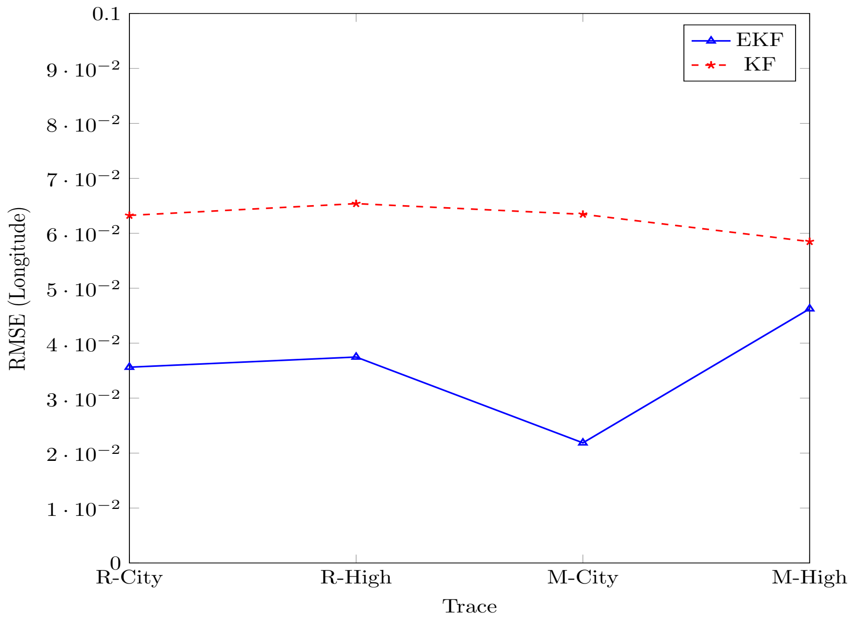


Figure. 4.20: Root Mean Square Error (RMSE) for longitude.

multiplication and inversion computation.

However, location precision has more priority over computational cost, as VANET computational device has enough resources to work with EKF.

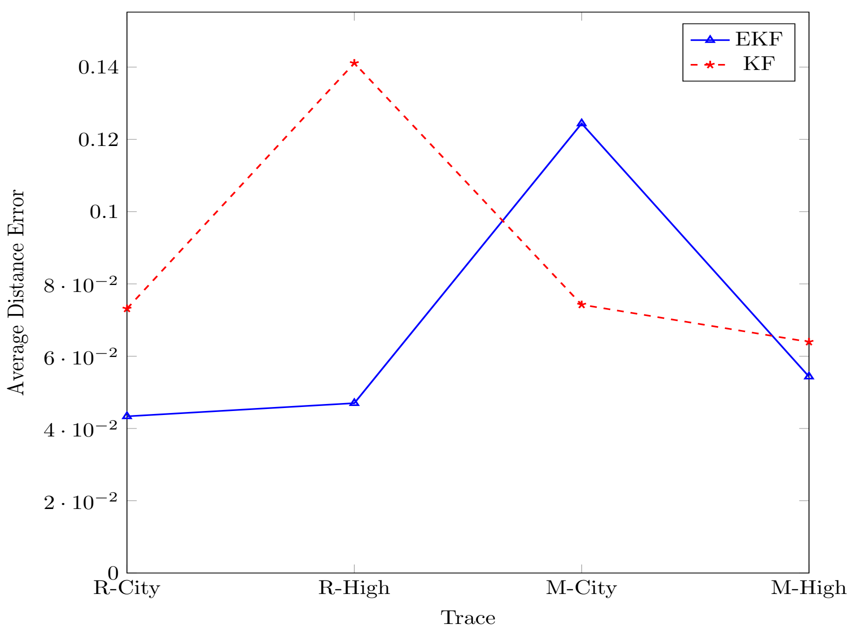


Figure. 4.21: Average Euclidean Distance Error (AEDE).

4.7 SUMMARY

Based on our experimental results, it is observed that location prediction using EKF for model based traces is almost equal to the measured location. However, coordinate system in model based traces is different from the GPS system. It is also observed in our simulation results that the performance of the location prediction using EKF is better on the highway compared to the city scenario.

With reference to the real traces, EKF prediction algorithm performs better on the highway compared to the city. However, it is lower than the model based traces. Nevertheless, model based traces are unrealistic to be used in real world scenarios, unlike real traces. In addition, DE is less on the highway with real and model based traces compared to the city. On comparison of DE between model and real based traces, it is found that the model based traces showed less error compared to the real traces. Velocity error is less with reference to model based traces on the highway compared to the real traces. Overall, EKF performs well in highway scenario as vehicle steering angle and speed and road layout do not change for the long time unlike city scenario.

On the basis of DE, RMSE, AEDE and VE results, it is also observed that the EKF based prediction outperforms the KF based prediction. Hence, it is concluded that the EKF based prediction should be used in VANET where location precision is more crucial, compared to KF based prediction. Though the time complexity of the EKF based prediction algorithm is discussed briefly in the subsection 4.6.5, nonetheless, it is a future work to analyze the time complexity of our EKF based prediction algorithm with reference to VANET.

Related Publication

- Raj K Jaiswal, Jaidhar C D **Location Prediction Algorithm for a Non-linear Vehicular Movement in VANET using Extended Kalman Filter** Wireless Networks, 2016, pages 1-16, issn 1572-8196,doi 10.1007/s11276-016-1265-4, url=http://dx.doi.org/10.1007/s11276-016-1265-4.

Chapter 5

Prediction Based Position-based Routing Protocol

The accuracy of a location is affected by several factors such as underpass, buildings, trees in the city. In addition, environmental effect also impact on location such as line-of-sight, signal interference. Consequently, the difference between real and GPS position affects the position-based routing protocols performance. Thus, to minimize the impact of location error, this chapter proposes prediction based position-based routing protocol. The salient contributions of the chapter are:

- It proposes prediction based position-based routing protocol using KF and EKF as a prediction module.
- The routing performance is evaluated on two different propagation models such as Two-ray ground and Winner-II on 250m and 500m transmission range using heterogeneous and homogeneous traffic environments for the model based traces.
- It computes the error removal capacity of KF by adding one time error into location.
- It predicts the advance location of the vehicle on highway by supplying one time latitude and longitude information to the KF module.
- It evaluates the routing protocol performance on two different propagation models viz. Two-ray ground and Winner-II only for 500m transmission range on real time GPS traces.
- It compares the performance of prediction based position-based routing protocol with CLWPR protocol on model based and real time GPS traces.

The remaining sections of this chapter are organized as follows: system model is discussed in Section 5.1 which is different from the system model discussed in Section 4.1 of Chapter 4. The proposed work is described in Section 5.3. The performance of the proposed protocol is evaluated in two different sections viz. Section Section 5.4 evaluates the performance of prediction based position-based routing protocol using model based mobility traces while Section 5.5 evaluates the performance of the protocol on real GPS traces. The simulation parameters and results are discussed separately in each section. Section 5.6 the summarizes the work.

5.1 SYSTEM MODEL AND ASSUMPTIONS

Each vehicle is outfitted with an on-board unit and a GPS device to retrieve location. The speed of the vehicle varies with traffic conditions. It is assumed that the vehicle heading gets changed either at a turning point or during the lane change. Thus, steering angle and acceleration do not change instantly. The vehicle state X is defined by four-tuple $[x,\ y,\ v_x,\ v_y]$ where x and y are the latitude and longitude position while v_x and v_y depict the speed towards latitude and longitude, respectively. It is assumed that location server is deployed at the prominent places or junction point to retrieve and register the vehicle location as a *location_id* with location server.

The change in vehicle state is measured by Equation (5.1) where Pos_{t-1}, V_{t-1} and a_{t-1} are the vehicle position, velocity and acceleration at $t-1$, while dt shows the time difference in change of velocity.

$$Pos_t = Pos_{t-1} + V_{t-1} * dt + \frac{1}{2} a_{t-1} dt^2 \tag{5.1}$$

Hence, the state model X of the vehicle is defined as:

$$X = \begin{bmatrix} x \\ y \\ v_x \\ v_y \end{bmatrix} = \begin{bmatrix} x_{t-1} + v_x * dt \\ y_{t-1} + v_y * dt \\ v_{x_{t-1}} \\ v_{y_{t-1}} \end{bmatrix} \tag{5.2}$$

Here, x_{t-1} and y_{t-1} are the state of the vehicle measured at $t-1$ and $v_{x_{t-1}}$, $v_{y_{t-1}}$ are the velocity components.

5.2 PARAMETERS OF KF AND EKF

KF and EKF are described in Chapter 4. However, in this chapter KF and EKF are designed and implemented by considering four system state which is different from the Chapter 4.

5.2.1 KF and EKF Implementation

In this work, KF and EKF are implemented in C++ programming language using Eigen library for linear algebra (Guennebaud et al. 2010) and incorporated as a prediction module in position-based routing protocol using NS-3.23 simulator.

5.2.1.1 KF Initialization

In Equation (4.5), w_{t-1} and u_{t-1} are assumed to be zero. To initialize KF, the following parameters are set to an initial value. The transition matrix A is initialized as:

$$A = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.3}$$

Where dt is taken as one second. H_t is defined based on measurement location z_t which provides the latitude and longitude position of the vehicle. Thus, H_t is:

$$H_t = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{5.4}$$

The initial state X is fixed at zero. The error covariance P_t^- should be large enough to minimize the error gap in state estimation. Thus P_t^- is:

$$P_t^- = \begin{bmatrix} 10000 & 0 & 0 & 0 \\ 0 & 10000 & 0 & 0 \\ 0 & 0 & 10000 & 0 \\ 0 & 0 & 0 & 10000 \end{bmatrix} \tag{5.5}$$

The process noise Q and measurement noise R are taken in an ad hoc manner to get the best estimation results (Bavdekar et al. 2011). Thus, Q and R are initialized as:

$$Q = \begin{bmatrix} 0.1 & 0 & 0 & 0 \\ 0 & 0.1 & 0 & 0 \\ 0 & 0 & 0.1 & 0 \\ 0 & 0 & 0 & 0.1 \end{bmatrix} \tag{5.6}$$

$$R = \begin{bmatrix} 0.001 & 0 \\ 0 & 0.001 \end{bmatrix} \tag{5.7}$$

5.2.1.2 EKF Initialization

To initialize EKF, F_t, W_t, H_t, V_t, P_t, Q and R parameters are initialized as follows:

$f(\hat{x}_{t-1}^{-}, 0, 0)$ is partially differentiated with respect to $\hat{x}_{t-1}^{-}$ to obtain Jacobian matrix F_t. Here, dt is assumed to be one. Thus F_t is initialized as follows:

$$F_t = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.8}$$

Similarly, $f(\hat{x}_{t-1}^{-}, 0, 0)$ is differentiated partially with respect to w_{t-1} to get W_t, however, w_{t-1} is taken as zero by assuming negligible error in the process model. Thus, in this experiment, W_t is taken as:

$$W_t = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{5.9}$$

On partial differentiation of $h(\hat{x}_t^{-}, v_t)$ with respect to $\hat{x}_t^{-}$ and v_t, Jacobian H_t and V_t are obtained on which are initialized as:

$$H_t = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.10}$$

and

$$V_t = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.11}$$

The initial values of P_t^-, Q and R are same as shown in Equations (5.5) to (5.7).

Though both the filters give quite reliable prediction, however, EKF predicted position is quite closer to the real position as compared to KF which is more useful in automatic parking and collision avoidance system and not in other fields such as routing which does not need as high as correct location in EKF (Jaiswal & Jaidhar 2016). Based on the experimental results, it is evident that KF and EKF take more running time as compared to the equation of motion. However, energy is not a constraint as computing device takes the energy from the vehicle battery. This paper uses both the filters as a prediction module in routing to confirm it.

Algorithm 1 Location prediction using KF/EKF

procedure KF/EKF PREDICTION
  Search (Destination *location_id* in *Neighbor_Table* at *t*)
  if (Destination *location_id* is found) **then**
    Compute (*location_id* using KF/EKF at *t+1*)
    Update (Current *location_id* ← Predicted *location_id*)
    Send (Packet with predicted *location_id* to the destination)
  else
    Send (Request to location server to get destination *location_id*)
    Search (Neighbor node *location_id*, closer to the destination)
    Compute (Neighbor node *location_id* using KF/EKF at *t+1*)
    Update (Current *location_id* ← Predicted *location_id*)
    Send (Packet to neighbor node with Predicted *location_id*)
  end if
end procedure

5.3 PREDICTION BASED POSITION-BASED ROUTING PROTOCOL

It uses the KF and EKF based prediction module into position-based routing protocol to minimize the location error. Each node broadcasts the *HELLO* packet to its neighbor nodes for every 1.5 seconds beyond this time limit topology may get changed. The *HELLO* packet remains in the *Neighbor_Table* up to 4.5 seconds or until location gets changed. It contains the information of the node such as *Node_id*, *location_id* and *Velocity*. Before sending the packet, a node identifies the destination node *location_id* in *Neighbor_Table*, on the availability of it, *location_id* is sent to KF and EKF module to get predicted *location_id* which is added to the destination *location_id* in the packet header. Upon unavailability of the destination *location_id* in the *Neighbor_Table*, source node obtains it from location server and then it searches the next neighbor node based on Euclidean distance which is closer to the destination and passes its *location_id* to KF and EKF to get predicted *location_id* as shown in Algorithm 1.

5.4 PERFORMANCE EVALUATION OF PREDICTION BASED POSITION-BASED ROUTING PROTOCOL USING MODEL BASED MOBILITY TRACES

This section evaluates the performance of the proposed routing protocol using model based mobility traces.

5.4.1 Simulation Parameters

This experiment uses CLWPR NS-3.23 patch which is a position-based routing protocol as explained in Section 2.5.2. In CLWPR, KF and EKF modules are used instead of the equation of motion based prediction, one by one. CLWPR routing parameters used in simulation are listed in Table 5.1, while parameters used in NS-3.23 are listed in Table 5.2. In addition, it is also assumed that the location servers are deployed at the prominent places and junction points to fetch vehicle location when it is not found in *Neighbor_Table*.

To see the effect of path loss on prediction, two different propagation models are used such as Two-ray ground and Winner-II models. In later propagation model, B1 scenario is taken in the experiment which implements more realistic path loss model for a city scenario as compared to Two-ray ground model more detail can be seen in (IST-WINNER 2007) work.

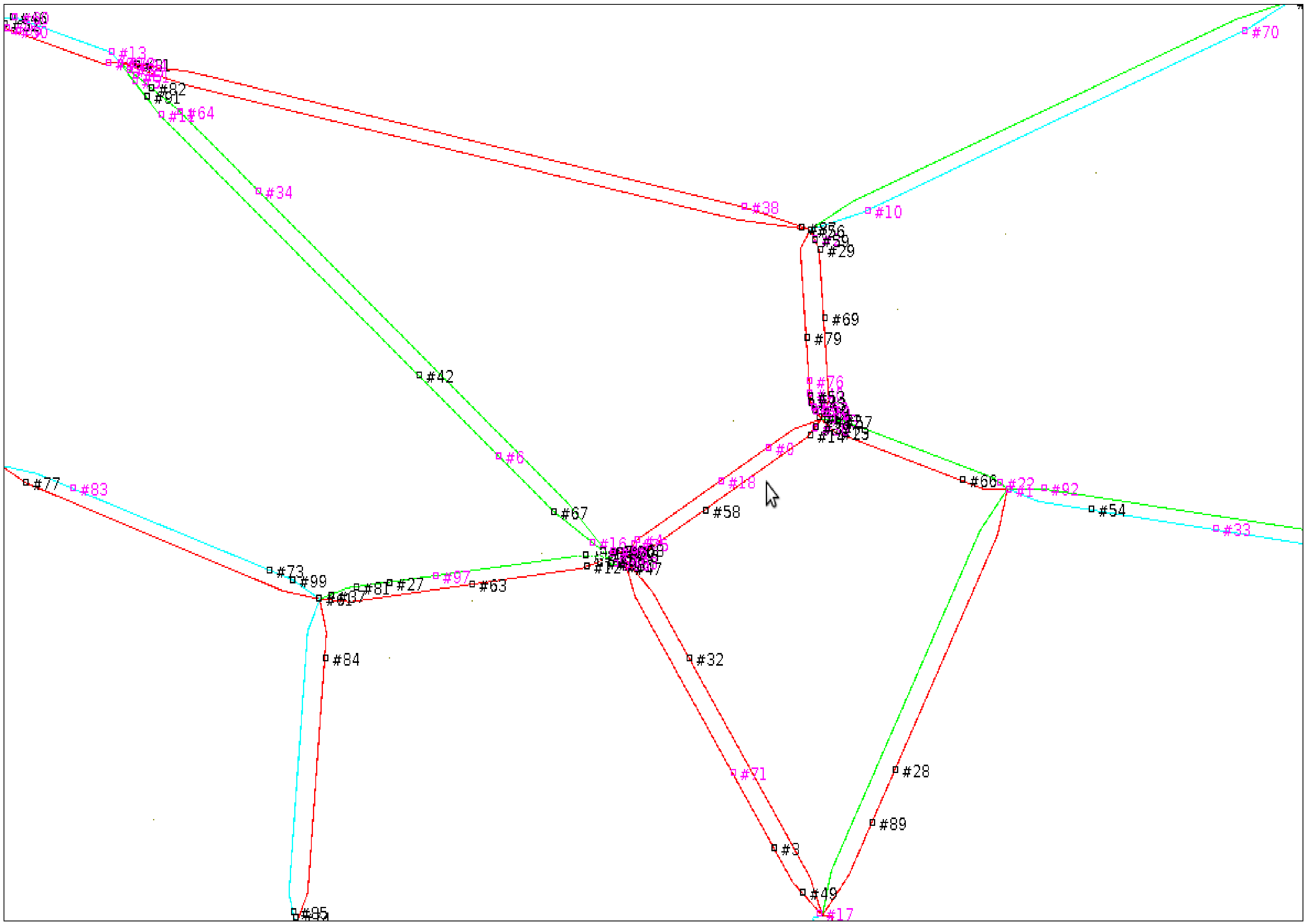


Figure. 5.1: City road layout

VANETMOBISIM is used to get the vehicular mobility for 25, 50, 75 and 100 vehicles which are deployed in the area of 1000 x 1000 m^2 for city and 30 x 2000 m^2 for the highway as shown in Figures 5.1 and 5.2. All the vehicles are connected using car following model. The number of vehicles remains constant in simulation during the simulation period. Further, homogeneous and heterogeneous traffic environments are used in mobility generation. The homogeneous traffic consists of cars with equal length. The parameters used to generate homogeneous traffic are enlisted in Tables 5.3a and 5.3b. The heterogeneous traffic environment consists of cars, trucks and buses as these vehicles run in the city with varying speed and have different acceleration and deceleration. In addition, vehicle body length also varies from vehicle to vehicle and these parameters are likely to affect the location prediction. The specific and common parameters considered for heterogeneous traffic are listed in Table 5.3d. Every node in simulation has independent location error which is introduced using Gaussian distribution.

Table 5.1: Routing parameters

CLWPR	**PROPOSED**
HelloInterval=1.5s	HelloInterval=1.5s
MaxQueueTime=10s	MaxQueueTime=10s
DynHello=False	DynHello=False
Prediction Module=Equation of motion	Prediction Module=KF and EKF

5.4.2 Results and Discussion

The performance of the routing protocol is evaluated on the metrics of PDR, AD and throughput and compared with CLWPR performance. The performance results are grouped into heterogeneous and homogeneous traffic environment for the city and highway scenarios which are further categorized in Two-ray ground and Winner-II models for each scenario. In the simulation results, it is found that KF and EKF both produce similar PDR, AD and throughput. Thus, EKF results are not shown with KF results due to similarity and to avoid the overlapping of the

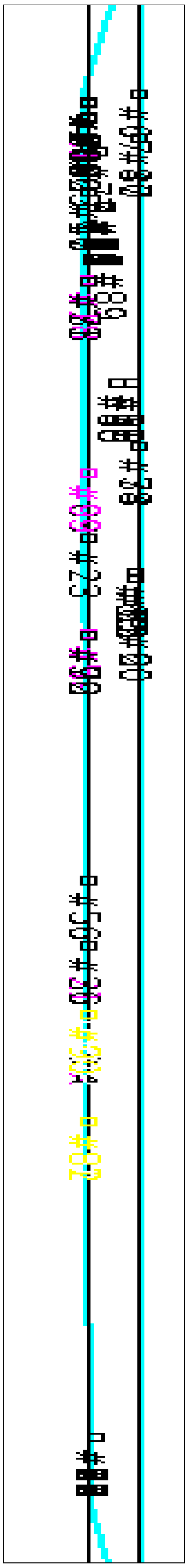


Figure. 5.2: Highway layout

Table 5.2: Network simulator parameters

Parameters	**Values**
Network Simulator	NS-3.23
Simulation Time (s)	300
Routing Protocols	CLWPR & PROPOSED
Antenna Model	Omni-Directional Antenna
Modulation Technique	OFDM
Radio Propagation Model	Winner-II and Two-ray Ground
Transmission Range (m)	250 & 500
MAC Type	IEEE 802.11p
MAC Rate	6 Mbps
Transport Protocol	UDP
Data Type	CBR
CBR Generation Rate(Kbps)	128
Packet Size	500 Bytes
No. of Connections	30% of the Total Number of Vehicles
No. of Vehicles	25, 50, 75, 100

images. However, EKF takes more time to complete the simulation, unlike KF due to the involvement of more computational steps such as computation of Jacobian. Section 5.4.2.3 is the common legend for all the results shown in Figures 5.3, 5.4 and 5.6 to 5.27 in which 250 and 500 are attached with protocols name to depict the transmission range. In addition, C and H are used as an acronym for the city and highway scenarios in figure caption:

5.4.2.1 PDR

Following subsections discuss the PDR in different scenarios in which vehicle have variable speed.

City based Heterogeneous Traffic

Figures 5.3 and 5.4 show the PDR on Two-ray ground and Winner-II propagation models for city based heterogeneous traffic, in which PROPOSED-250 has 52% PDR with 25 nodes while CLWPR-250 has 54% PDR and it is reduced to 14% for PROPOSED-250 and 13% for CLWPR-250 with 100 nodes using Two-

Table 5.3: Mobility parameters

(a) Common parameters

Description	Values
Simulator	VANETMOBISIM
Simulation Time (s)	499
Simulation Area (City)	1000 x 1000 m^2
Simulation Area (Highway)	30 x 2000 m^2
Traffic lights (City)	10
Traffic Light Duration (s)	60
No. of Lanes	2
Min. Congestion Distance	$2m$
Traffic Type	Heterogeneous Homogeneous

(b) Specific parameters for car

Description	Values
Percentage in Traffic	60
Min. Velocity (m/s)	0.1
Max. Velocity (m/s)	25
Driver Politeness Factor	0.8
Max. Acceleration	0.9 (m/s^2)
Max. Deceleration	0.6 (m/s^2)
Vehicle Length (m)	4
Safe Headway Time (s)	2

(c) Specific parameters for bus

Description	Values
Percentage in Traffic	30
Min. Velocity (m/s)	0.1
Max. Velocity (m/s)	17
Driver Politeness Factor	0.4
Max. Acceleration	0.5 (m/s^2)
Max. Deceleration	0.3 (m/s^2)
Vehicle Length (m)	8
Safe Headway Time (s)	5

(d) Specific parameters for truck

Description	Values
Percentage in Traffic	10
Min. Velocity (m/s)	0.1
Max. Velocity (m/s)	11
Driver Politeness Factor	0.2
Max. Acceleration	0.3 (m/s^2)
Max. Deceleration	0.5 (m/s^2)
Vehicle Length (m)	12
Safe Headway Time (s)	10

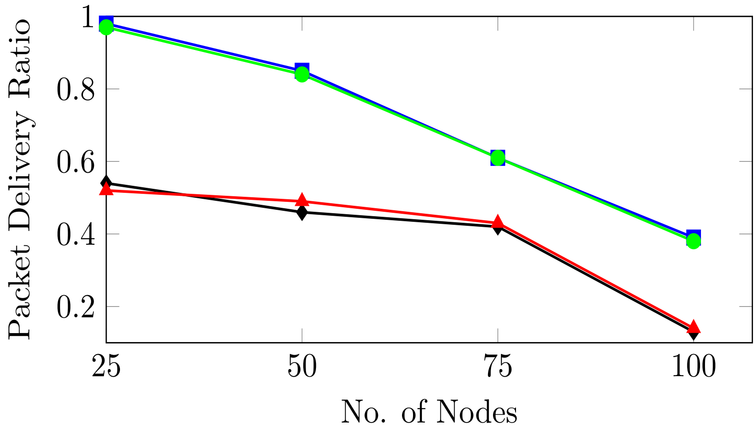


Figure. 5.3: PDR on Two-ray ground model (C-Heterogeneous Traffic)

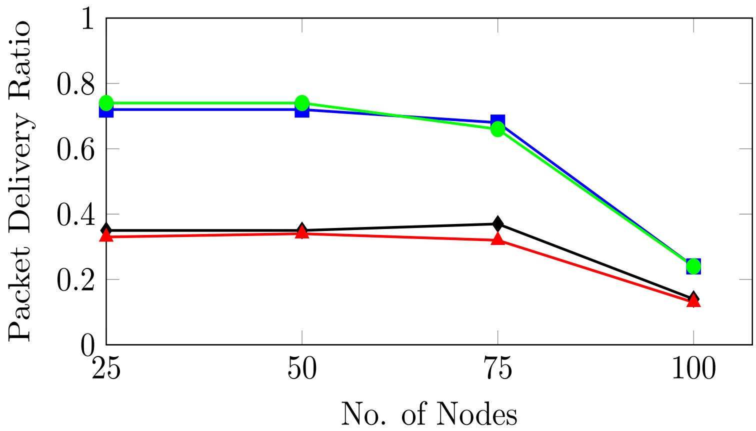


Figure. 5.4: PDR on Winner-II model (C-Heterogeneous Traffic)

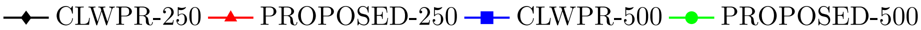


Figure. 5.5: Common legend for the results

ray ground model. However, PROPOSED-250 improves the PDR with 50 and 75 nodes compared to CLWPR as shown in Figure 5.3. With 500 transmission range on Two-ray ground, due to location prediction technique, CLWPR-500 does better compared to PROPOSED-500.

With reference to Winner-II model, using location prediction. Overall, PROPOSED-500 has 2.12% more PDR compared to CLWPR-500, while PROPOSED-250 has 8% less PDR compared to CLWPR-250 in 250m transmis-

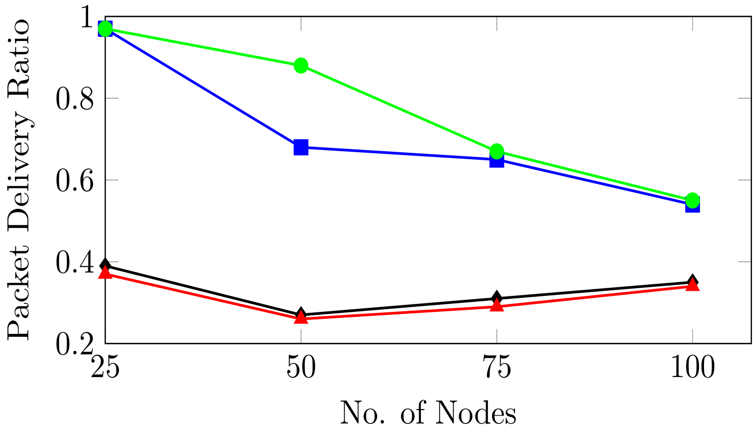


Figure. 5.6: PDR on Two-ray ground model (H-Heterogeneous Traffic)

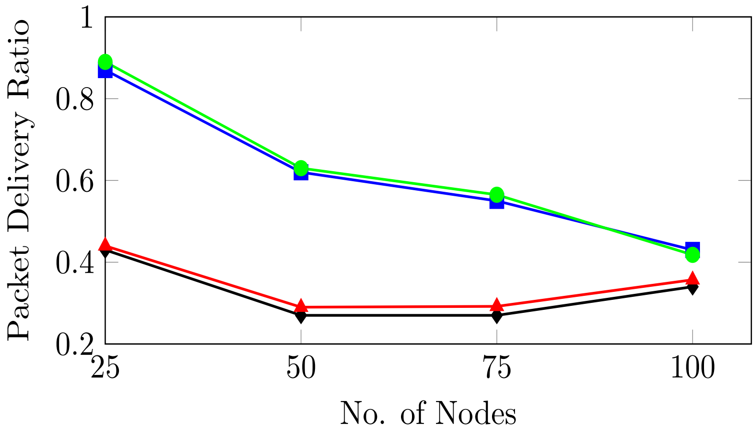
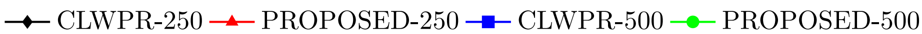


Figure. 5.7: PDR on Winner-II model (H-Heterogeneous Traffic)



sion range as shown in Figure 5.4.

City based Homogeneous Traffic

With reference to homogeneous traffic environment, it is found that PROPOSED protocol has better PDR almost in all types of network, compared to CLWPR. PROPOSED-250 and CLWPR has 56% and 54% PDR in 25 nodes using Two-ray ground model. However, PDR decreases as the number of nodes increases. PROPOSED-500 and CLWPR-500 has 94.9% and 95.7% PDR with 25 nodes. However, PROPOSED-500 improves the PDR compared to CLWPR

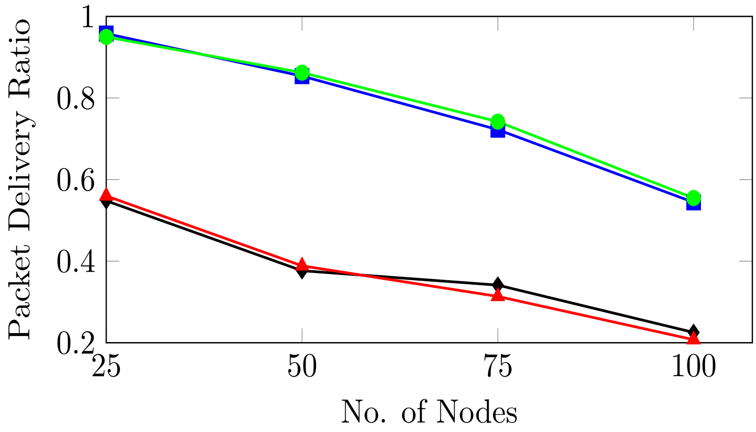


Figure. 5.8: PDR on Two-ray ground model (C-Homogeneous Traffic)

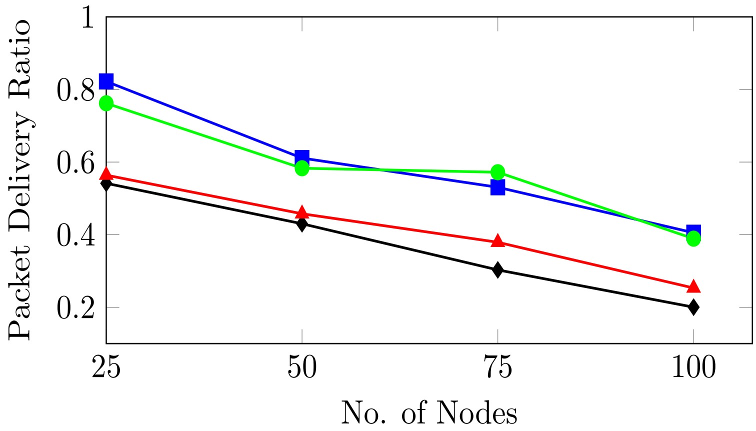
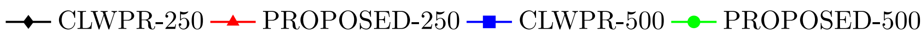


Figure. 5.9: PDR on Winner-II model (C-Homogeneous Traffic)



with increasing number of nodes as shown in Figure 5.8. Using Winner-II model, it is observed that PROPOSED-250 performs better compared to CLWPR-250 from sparse to dense network, whereas PROPOSED-500 can not perform better in the sparse network as shown in Figure 5.9. On comparison between Figures 5.3 and 5.8 and Figures 5.4 and 5.9, it is found that prediction improves the routing performance in both the traffic environment for the city scenario.

Highway based Heterogeneous Traffic

From Figure 5.6, it is obvious that the PROPOSED-500 has better PDR com-

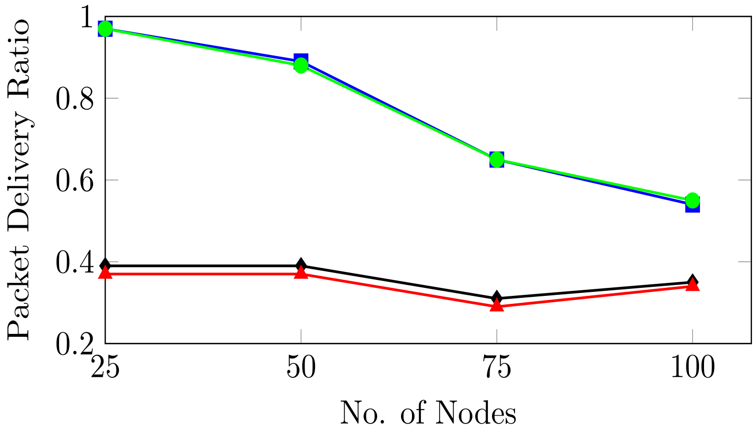


Figure. 5.10: PDR on Two-ray ground model (H-Homogeneous Traffic)

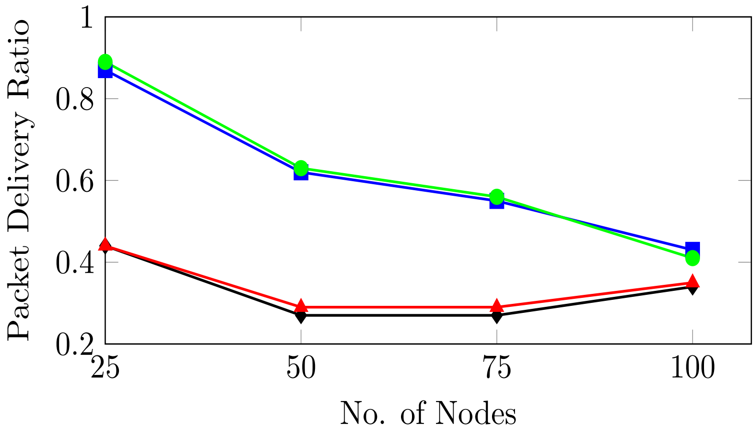
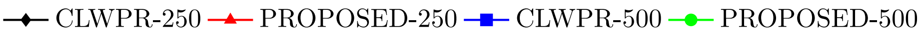


Figure. 5.11: PDR on Winner-II model (H-Homogeneous Traffic)



pared to CLWPR-500 unlike 250m transmission range wherein CLWPR-250 has more PDR. With Winner-II in both the transmission range PROPOSED-250 and 500 have more PDR as shown in Figure 5.7.

Highway based Homogeneous Traffic

With homogeneous traffic in the highway scenario proposed protocol improves the PDR in all scenarios except PROPOSED-250 as shown in Figures 5.10 and 5.11. On comparison with Figures 5.6 and 5.10 and Figures 5.7 and 5.11, it is found that prediction is more accurate in heterogeneous traffic in the highway scenario. Though, prediction improves the PDR in most of the scenarios, however, it is observed that PDR decreases with increasing number of nodes in all scenarios in both the protocols.

5.4.2.2 Throughput

It measures the average number of bits received per second by each node.

City based Heterogeneous Traffic

Figures 5.12 and 5.13, show the throughput performance in heterogeneous city traffic. In Figure 5.12, PROPOSED-250 has 2.17% more throughput than CLWPR-250. With reference to 500m transmission range both the protocols have equal throughput on Two-ray ground model with 75 and 100 nodes, while PROPOSED-500 has less throughput with 25 and 50 nodes due to prediction. For 25 nodes, PROPOSED-250 gives 66.30 kbps, while CLWPR-250 gives 67.9 kbps throughput and PROPOSED-250 improves the PDR compared to CLWPR-250 as the number of node increases. Eventually, it reaches to 13.5 kbps and 11 kbps for PROPOSED-250 and CLWPR-250 with 100 nodes, respectively. Throughput is almost similar with 500m transmission range in both the protocols. With reference to Winner-II model, in 500m transmission range throughput is better compared to CLWPR, while CLWPR gives better throughput in 250m range (refer to Figure 5.13).

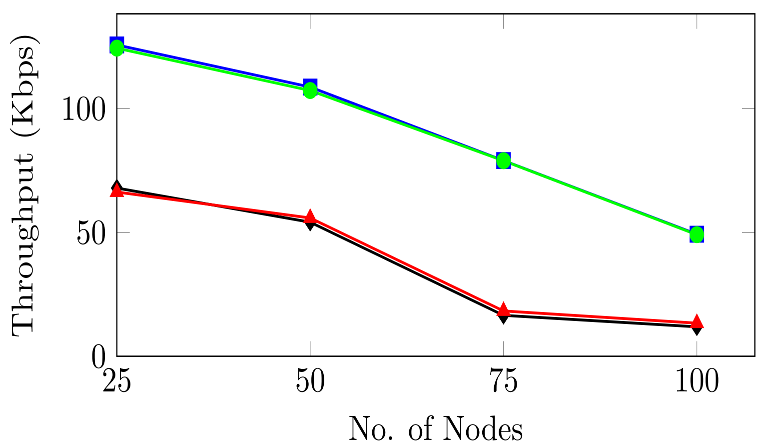


Figure. 5.12: Throughput on Two-ray ground model (C-Heterogeneous Traffic)

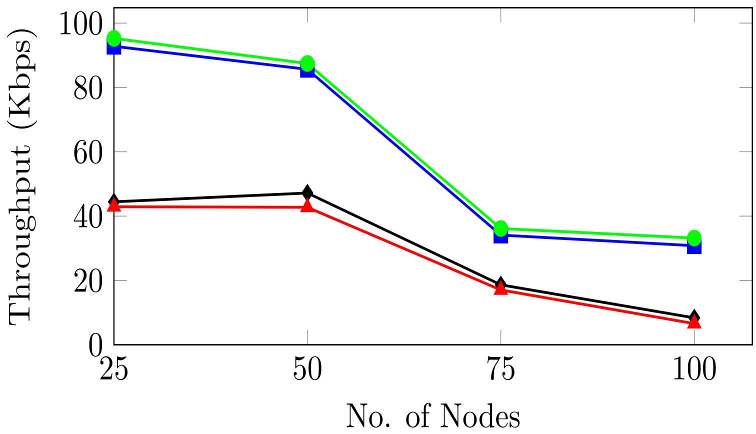


Figure. 5.13: Throughput on Winner-II (C-Heterogeneous Traffic)

CLWPR-250 PROPOSED-250 CLWPR-500 PROPOSED-500

City based Homogeneous Traffic

From Figure 5.16, it is evident that PROPOSED-250 has 2.12% and 2.35% more throughput with 25 and 50 nodes on Two-ray ground model, respectively. However, it decreases with 75 and 100 nodes. 71.61 kbps and 70.01 kbps are the maximum throughput with 25 nodes for PROPOSED-250 and CLWPR-250, while with 100 nodes 26.51 kbps and 28.62 kbps minimum throughput is observed, respectively. However, PROPOSED protocol has more throughput than CLWPR in 500m range.

With Winner-II model, throughput is more using PROPOSED-250 and PROPOSED-500, in all scenarios. 105.40 kbps and 97.10 kbps are the maximum throughput with 25 nodes using PROPOSED-500 and CLWPR-500, respectively, while it is 50.85 kbps and 47.09 kbps minimum throughput with 100 nodes (refer to Figure 5.17). In both the Figures 5.16 and 5.17 throughput decreases as the number of node increases. Throughput is more in homogeneous traffic compared to heterogeneous traffic (refer to Figures 5.12, 5.13, 5.16 and 5.17).

Highway based Heterogeneous Traffic

In both the propagation model throughput is improved. 48.46 kbps and 50.45 kbps are the maximum throughput with 25 nodes on Two-ray ground model for

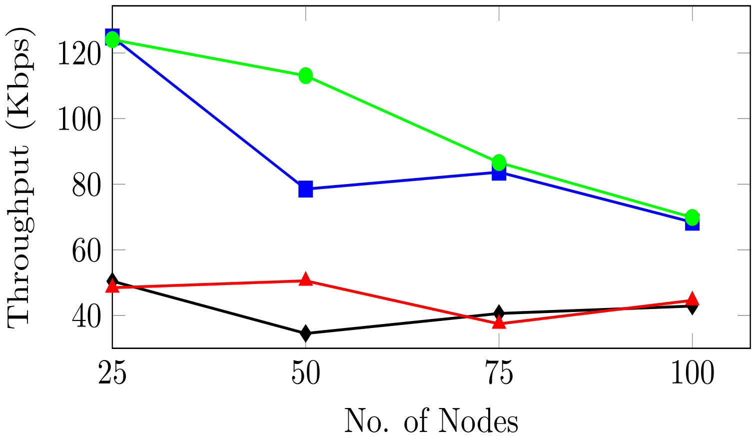


Figure. 5.14: Throughput on Two-ray ground model (H-Heterogeneous Traffic)

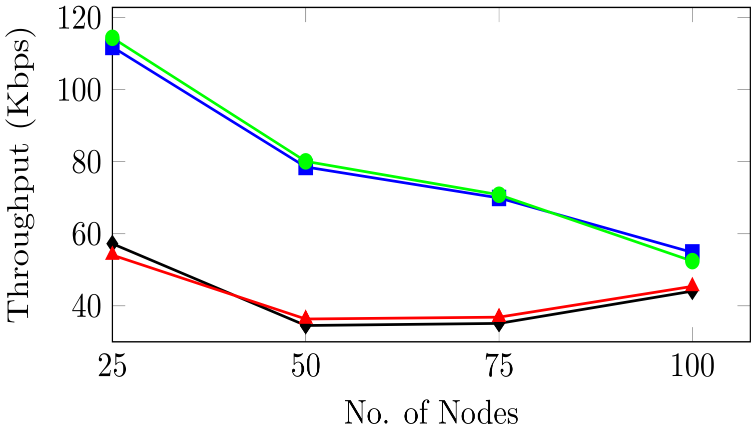
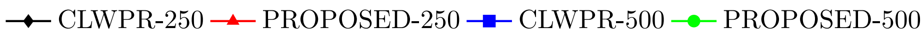


Figure. 5.15: Throughput on Winner-II (H-Heterogeneous Traffic)



PROPOSED-250 and CLWPR-250, however, proposed model improves the performance as node increases. 44.46 kbps and 42.86 kbps are the observed throughput with 100 nodes for PROPOSED-250 and CLWPR-25 which shows the growing trend compared to 50 and 75 nodes. This growth in throughput is due to the destination availability for a longer period in the proximity of the source. Throughput is improved with PROPOSED-500 compared to CLWPR-500 as shown in Figure 5.14.

With reference to Winner-II model, 111.84 kbps and 114.36 kbps are the maximum throughput for PROPOSED-500 and CLWPR-500 with 25 nodes, while it

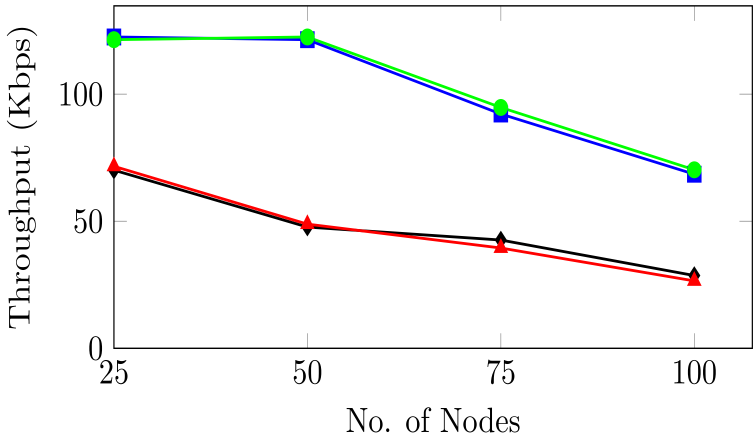


Figure. 5.16: Throughput on Two-ray ground model (C-Homogeneous Traffic)

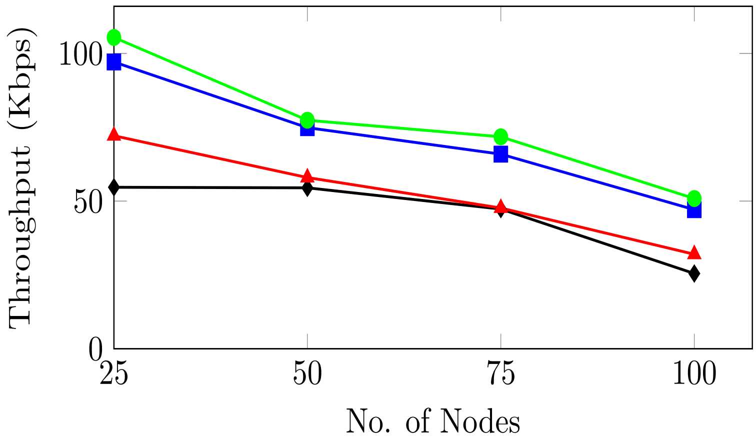
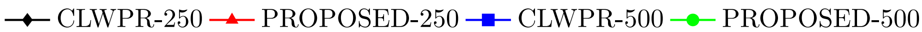


Figure. 5.17: Throughput on Winner-II (C-Homogeneous Traffic)



is as minimum as 54.81 kbps and 52.39 kbps with 100 nodes for CLWPR-500 and PROPOSED-500, respectively, as shown in Figure 5.15.

Highway based Homogeneous Traffic

50.45 kbps, 48.46 kbps, 124.87 kbps and 124.07 kbps minimum throughput is observed with 25 nodes for CLWPR-250, PROPOSED-250, CLWPR-500 and PROPOSED-500, respectively. With Two-ray ground model, it reaches to maximum 44.86 kbps, 42.61 kbps and 68.43 kbps and 69.88 kbps in the same sequence as shown in Figure 5.18.

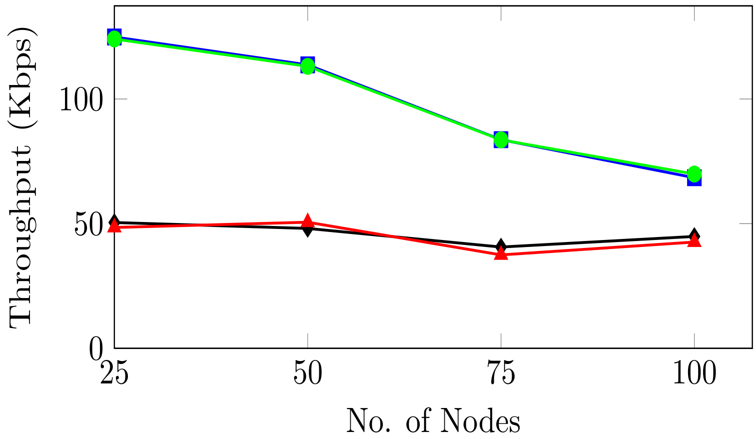


Figure. 5.18: Throughput on Two-ray ground model (H-Homogeneous Traffic)

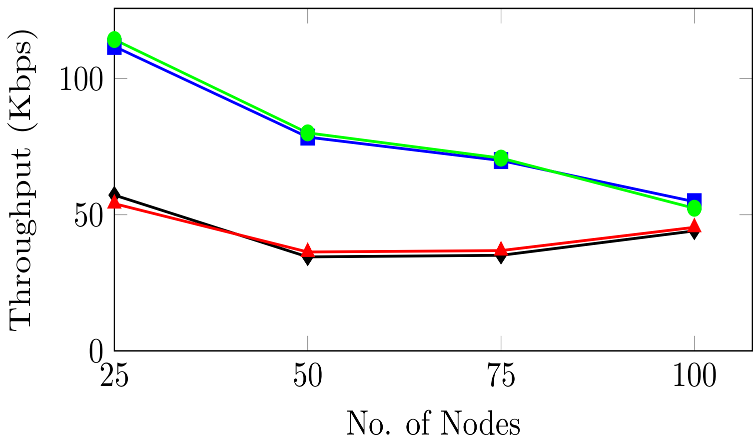
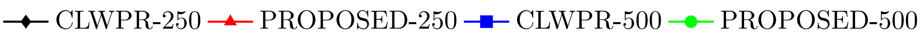


Figure. 5.19: Throughput on Winner-II (H-Homogeneous Traffic)



With reference to Winner-II model, 57.22 kbps, 54.08 kbps, 111.84 kbps and 114.36 kbps are the maximum throughput with 25 nodes for CLWPR-250, PROPOSED-250, CLWPR-500 and PROPOSED-500, respectively. In the same order 44.06 kbps, 45.38 kbps, 54.81 kbps and 52.39 kbps are the minimum throughput 100 nodes as shown in Figure 5.19. Both the scenarios show the improved throughput.

5.4.2.3 AD

AD measures the end-to-end transmission delay for correctly received packet between two communicating nodes. Since location prediction technique estimates the probable location of the nodes, thus, it minimizes AD by providing an accurate location. Figures 5.20 to 5.27 show the AD with different scenarios described as follows:

City based Heterogeneous Traffic

From Figures 5.20 and 5.21, it is evident that the prediction in routing minimizes AD. With 25 nodes measured average delays are 0.1743 ms, 0.0536 ms, 0.0023 ms and 0.0024 ms for CLWPR-250, PROPOSED-250, CLWPR-500 and PROPOSED-500, respectively on Two-ray ground model, while it increases as number of nodes increases and the maximum AD is recorded with 100 nodes which are 1.3753 ms, 0.8620 ms, 1.1589 ms and 1.13754 ms in the same order as shown in Figure 5.20.

On Winner-II model, the minimum delay is recorded as 0.2417 ms, 0.02714 ms, 0.0357 ms and 0.0384 ms for the aforementioned sequence with 25 nodes, while it increases with 100 nodes to 0.4488 ms, 0.4876 ms, 1.2132 and 1.0894 ms as shown in Figure 5.21.

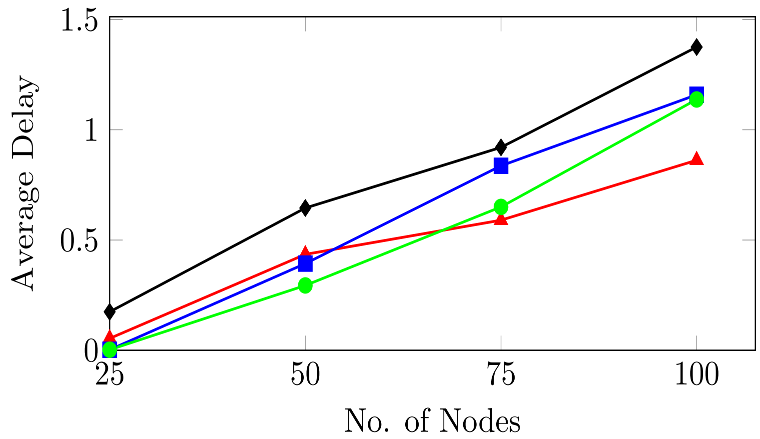


Figure. 5.20: AD on Two-ray ground model (C-Heterogeneous Traffic)

City based Homogeneous Traffic

With homogeneous traffic, proposed routing protocol minimizes the AD compared to CLWPR as shown in Figures 5.24 and 5.25. With reference to Two-ray

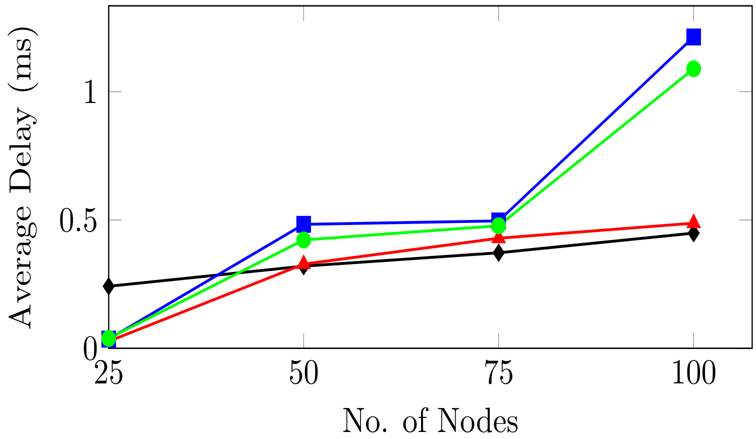
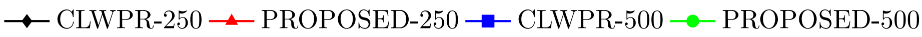


Figure. 5.21: AD on Winner-II model (C-Heterogeneous Traffic)



ground model, the minimum delay is observed with 25 nodes which are 0.1994 ms, 0.1654 ms, 0.0132 ms and 0.0628 ms for CLWPR-250, PROPOSED-250, CLWPR-500 and PROPOSED-500, respectively, while in similar manner, it increases in 100 nodes to 1.5315 ms, 1.3509 ms, 1.1368 ms and 1.0659 ms (refer to Figure 5.24).

On Winner-II model, the minimum observed delays are 0.1449 ms, 0.1165 ms, 0.2189 ms and 0.1567 ms, and maximum observed delays with 100 nodes are 1.036 ms, 0.6910 ms, 1.376 ms and 1.367 ms (refer to Figure 5.25). Overall, Two-ray ground model minimizes the AD compared to Winner-II model.

Highway based Heterogeneous Traffic

Minimum delay in this scenario for CLWPR-250, PROPOSED-250, CLWPR-500 and PROPOSED-500 is 0.1743 ms, 0.053 ms, 0.0024 ms and 0.0023 ms, while the maximum is 0.9453 ms, 0.8620 ms, 0.8589 ms and 0.7754 ms, respectively with Two-ray ground model (refer to Figure 5.22). Similarly, with Winner-II model minimum observed delays are 0.1614 ms, 0.1743 ms, 0.006 ms and 0.007 ms with 25 nodes, while maximum delays are 0.6634 ms, 0.4977 ms and 0.9473 ms, 0.8572 ms with 100 nodes as shown in Figure 5.23.

Highway based Homogeneous Traffic

In this scenario with 50 and 75 nodes PROPOSED-250 increases the AD com-

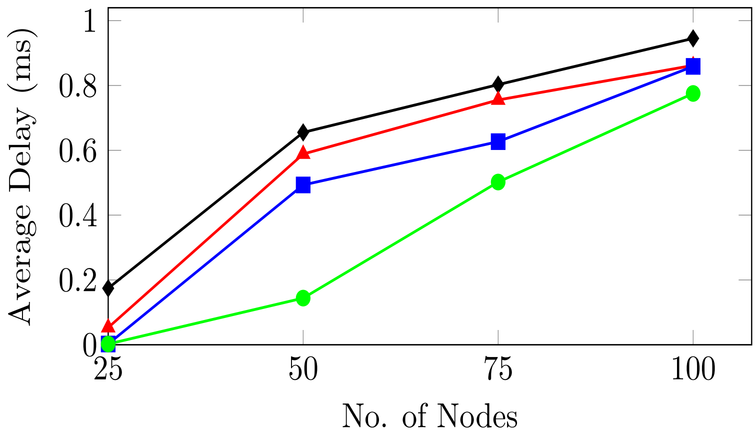


Figure. 5.22: AD on Two-ray ground model (H-Heterogeneous Traffic)

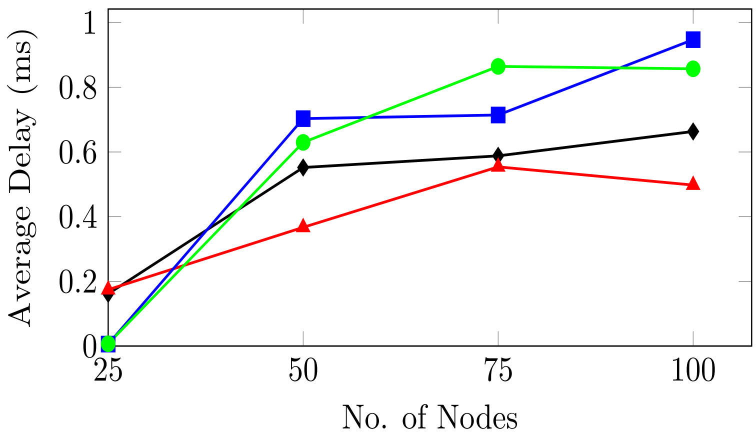


Figure. 5.23: AD on Winner-II model (H-Heterogeneous Traffic)

CLWPR-250 PROPOSED-250 CLWPR-500 PROPOSED-500

pared to CLWPR with Two-ray ground and Winner-II models, respectively. Apart from these exceptions, overall, prediction has reduced the delay in all other scenarios. The minimum delays observed for CLWPR-250, PROPOSED-250, CLWPR-500 and PROPOSED-500 are 0.1743 ms, 0.0536 ms, 0.0024 ms and 0.0023 ms, while maximum delays are 0.9453 ms, 0.762 ms, 0.9789 ms and 0.75 ms with Two-ray ground model (refer to Figure 5.26). Likewise, with reference to Winner-II model, the minimum delays are 0.1714 ms, 0.1643 ms, 0.2189 ms and 0.0072 ms, while the maximum delays are 1.558 ms, 1.364 ms, 0.9473 ms and 0.8572 ms (refer to Figure 5.27).

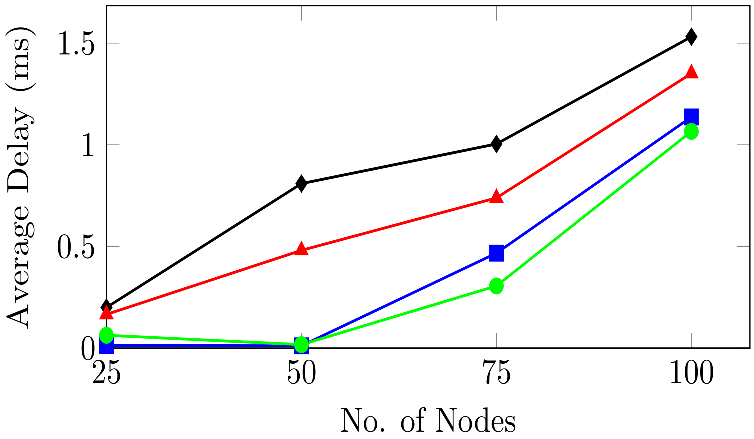


Figure. 5.24: AD on Two-ray ground model (C-Homogeneous Traffic)

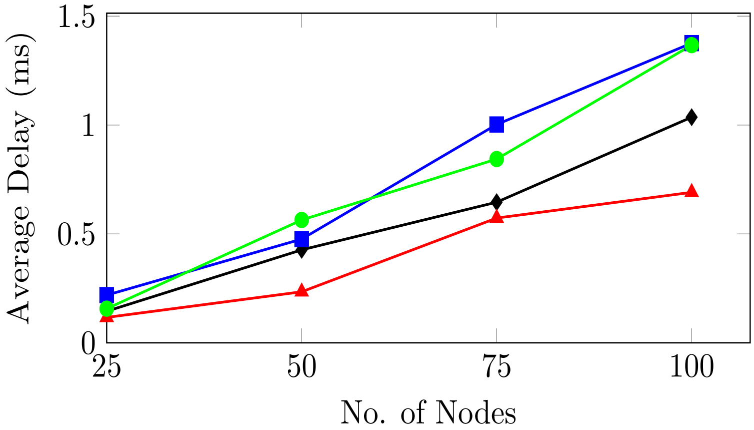
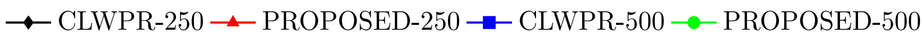


Figure. 5.25: AD on Winner-II model (C-Homogeneous Traffic)



5.5 PERFORMANCE EVALUATION OF PREDICTION BASED POSITION-BASED ROUTING PROTOCOL USING REAL GPS TRACES

This section evaluates the performance of the prediction based position-based routing protocol using real time GPS traces. Based on the results of Section 5.4, herein, only KF is used in prediction based position-based routing compared to EKF, due to similar performance and more computation time. It also evaluates and compares the protocol performance on simulator generated mobility for the

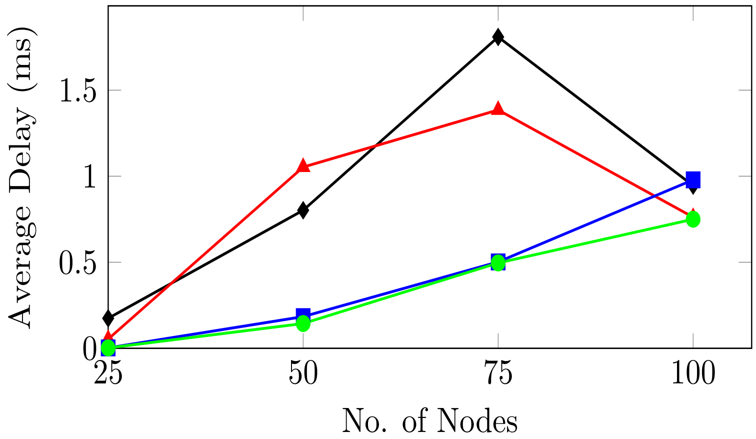


Figure. 5.26: AD on Two-ray ground model (H-Homogeneous Traffic)

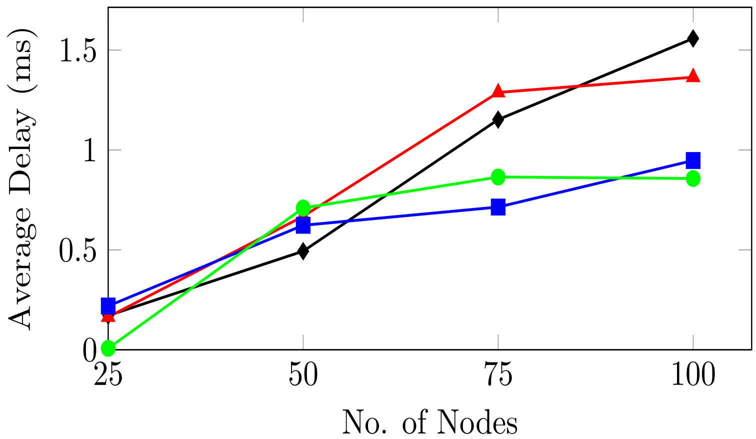
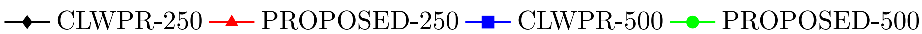


Figure. 5.27: AD on Winner-II model (H-Homogeneous Traffic)



heterogeneous traffic on 500m transmission range. In this experiment homogeneous traffic is not considered due to real traffic which will be always heterogeneous in nature. The simulation and routing parameters used in this experiment are explained in section 5.5.1 and Section 5.5.2 respectively, while system model is explained in Section 5.1.

5.5.1 Simulation Parameters

This work simulation parameters are similar to Chapter 5 except the real time GPS traces. The real time GPS traces are obtained from (rti 2016) which maintains archive for the real time GPS traces of the vehicles running in San Francisco city. Since real GPS traces are not compatible to work with NS-3.23 simulator due to time and unstructured data format. Thus, a python based parser is developed to convert the real GPS traces into NS-3.23 simulator compatible traces. After the conversion, consecutive 25, 50, 75 and 100 nodes are picked out among 1000 nodes. In this work, two different simulation time is used viz. with simulator generated mobility it is 300s, while it is 875s with real GPS traces to cover the entire time of the traces. With both the traces during simulation, to see the effect of path loss on prediction, Two-ray ground and Winner-II propagation models are used on 500m transmission range. In Winner-II model, B1 scenario is considered which implements more realistic path loss model for a city scenario compared to Two-ray model more detail can be seen in IST-WINNER (2007) work.

5.5.2 Results and Discussion

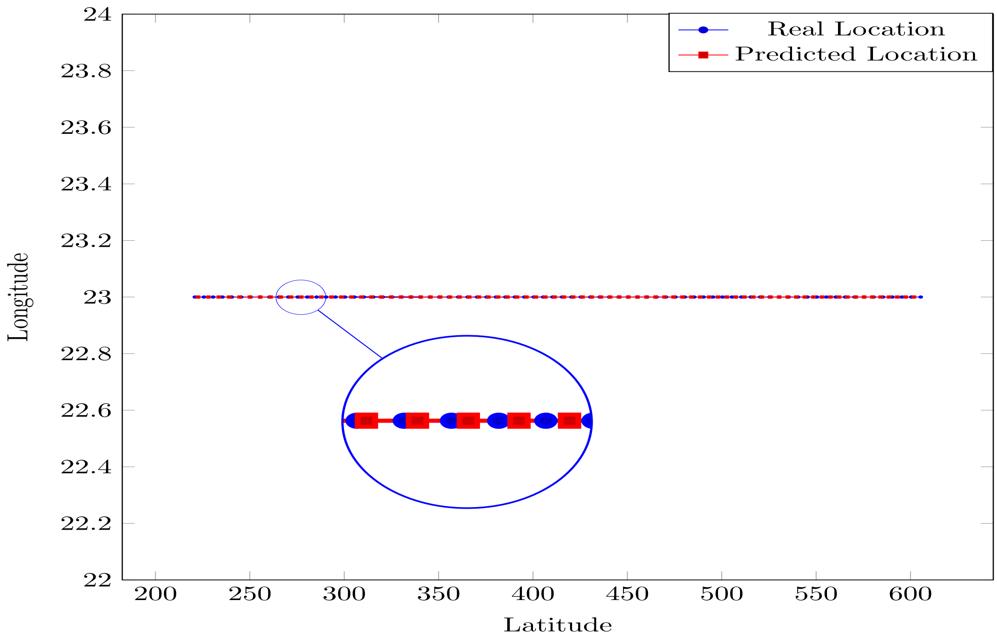


Figure. 5.28: Advance location prediction on the highway

Figure 5.28 depicts the advance location prediction of the vehicle position on the highway. The speed of the vehicle is kept constant at 10 m/s. Mobility is gen-

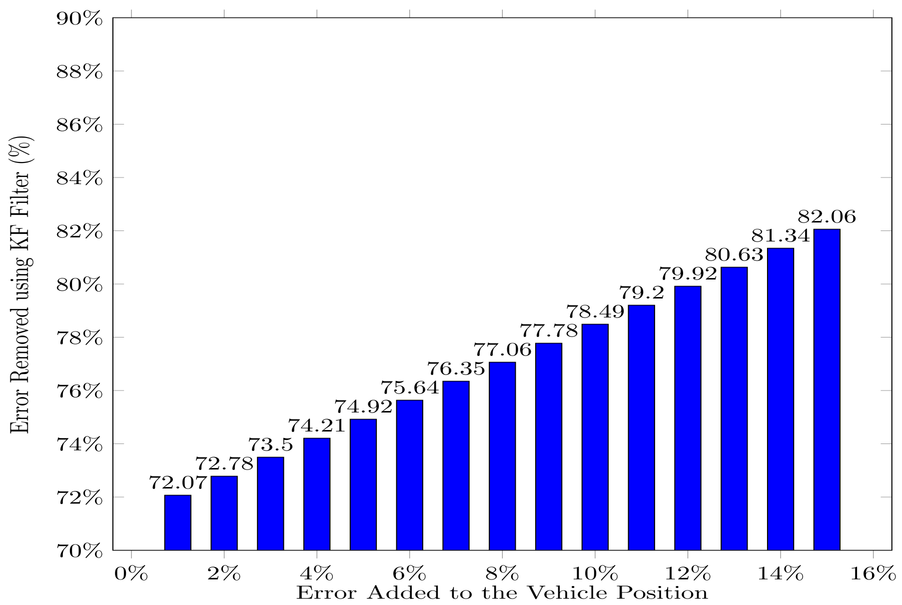


Figure. 5.29: Error removal capacity

erated using VANETMOBISIM in which only latitude position is getting changed while longitude is kept constant to resemble a scenario for a highway. Q and R parameters are tuned to get the best estimation. To get an advance movement prediction of the vehicle on a highway, one-time latitude (x)=216.2585823641 and longitude (y)=23.000001 information supplied to the KF module, based on this information KF predicts the advance movement of the vehicle. More details related to each position in advance prediction can be seen in Appendix I which consist the real x, real y, pre x, pre y, DE and difference between real and predicted position. However, advance prediction is not possible in the city scenario due to certain reasons. Firstly, it is unlikely that the vehicle will run with constant speed in the city, secondly, the city road network will not be straight for a long distance. Based on these notes and results, advance prediction is possible only with the highway scenario.

Figure 5.29 shows the error removal capacity of the KF. One time error is added to the x and y positions. From Figure 5.29, it is evident that 72.07% of error is removed on the addition of one percent error. The error removing capacity is increased as error increases.

The performance of the protocol is computed according to the different mobility and propagation model used in simulation. The routing performance is evaluated on the metrics of PDR, average delay and throughput and compared with the performance of CLWPR. In Figures 5.30 to 5.41, T and W are used with routing protocol as an acronym for Two-ray ground and Winner-II model, respectively. The results are discussed as follows:

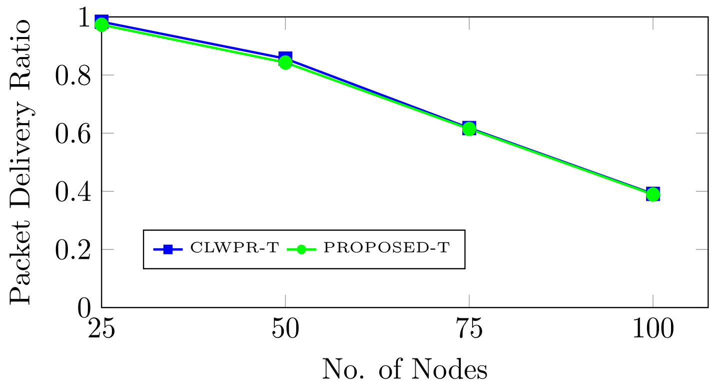


Figure. 5.30: PDR on simulator generated mobility (Two-ray ground model)

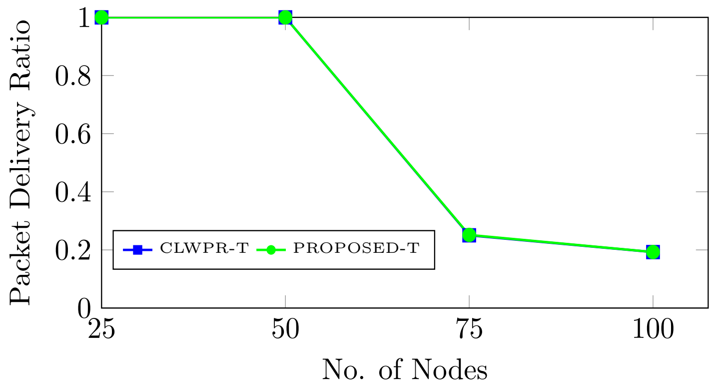


Figure. 5.31: PDR on real GPS traces (Two-ray ground model)

5.5.2.1 PDR

PDR of the proposed routing is computed on Winner-II and Two-ray ground propagation models for 500m transmission range. Figure 5.30 shows the PDR on simulator generated mobility on Two-ray ground model, it is observed that the

PROPOSED-T has 97.31% PDR for 25 nodes while CLWPR-T has 98.1% PDR. These differences remain the same for other scenarios too. Overall PROPOSED-T could not improve the PDR on Two-ray ground model with 500m transmission range with simulator generated mobility.

With reference to real GPS traces, PROPOSED-T and CLWPR-T both have

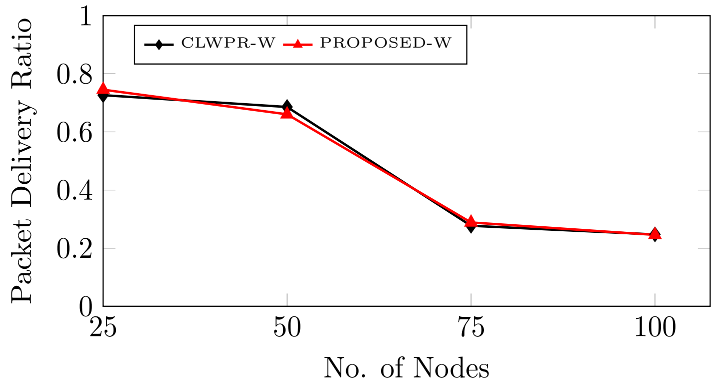


Figure. 5.32: PDR on simulator generated mobility (Winner-II model)

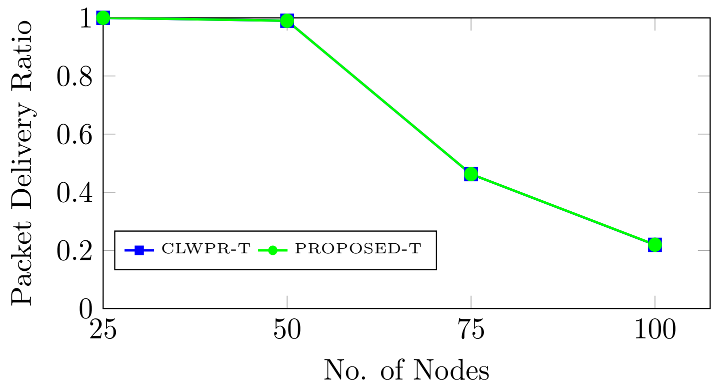


Figure. 5.33: PDR on real GPS traces (Winner-II model)

100% PDR for 25 and 50 nodes, it decreases as the number of nodes increases. With 75 nodes, CLWPR-T has 61.7% PDR, while it is 61.4% with PROPOSED-T. With 100 nodes CLWPR-T has 39% and 38.9% with PROPOSED-T. From Figure 5.31, it is evident that KF based prediction and equation of motion based prediction has quite reliable and equal PDR up to 50 nodes on real GPS traces compared to simulator generated mobility as shown in Figures 5.30 and 5.31. Generally, it is observed that PDR decreases as the number of node increases, however with real GPS traces adverse results are shown. Up to 50 nodes, PDR remain constant to 100%, while a steep fall in PDR can be seen with 75 and 100 nodes. On comparison with real GPS traces and simulator generated mobility, a gradual decrement is observed with latter scenario.

With reference to Winner-II model on simulator generated mobility,

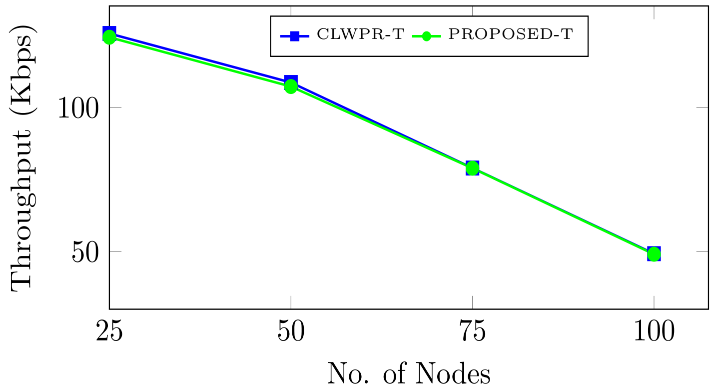


Figure. 5.34: Throughput on simulator generated mobility (Two-ray ground model)

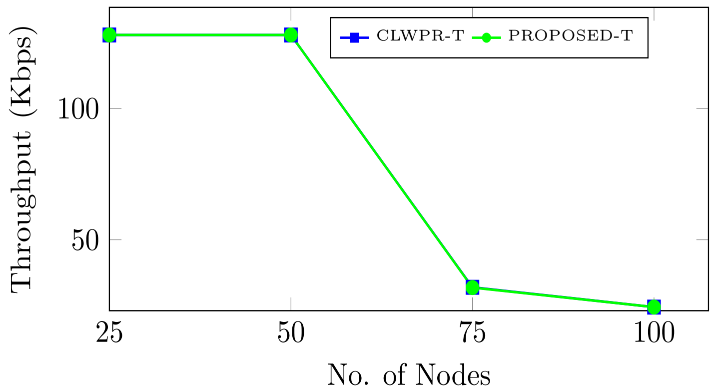


Figure. 5.35: Throughput on real GPS traces (Two-ray ground model)

PROPOSED-W has 74.53% PDR for 25 nodes while CLWPR-W has 72.6% PDR. In both the routing protocols PDR decreases as node number increases. With 75

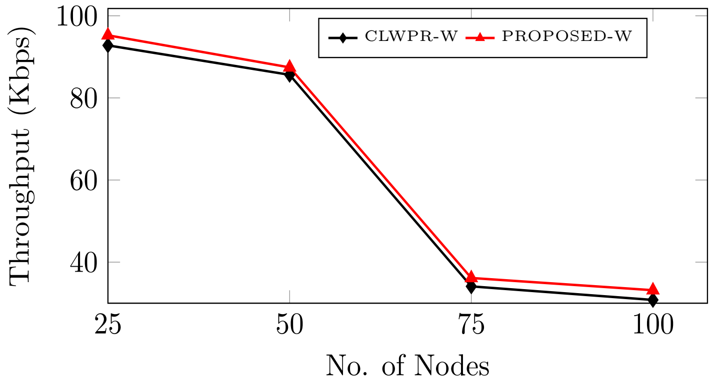


Figure. 5.36: Throughput on simulator generated mobility (Winner-II model)

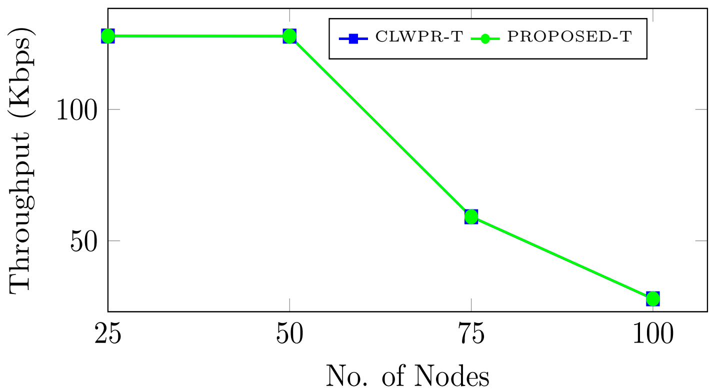


Figure. 5.37: Throughput on real GPS traces (Winner-II model)

nodes, there is a slight improvement in PDR in PROPOSED-W which is 28.8% compared to 27.7% of CLWPR-W. With 100 nodes, it is noticed that CLWPR-W and PROPOSED-W have 24.7% and 24.5% PDR, respectively. Based on these results, PROPOSED-W improves the PDR up to 75 nodes compared to CLWPR-W in 500m transmission range as shown in Figure 5.32.

With reference to real GPS traces on Winner-II model, PROPOSED-W and CLWPR-W both have stable PDR up to 50 nodes which are 100% for 25 nodes and 99% for 50 nodes. For 75 nodes PROPOSED-W and CLWPR-W have 46.24% and 46.23% PDR, a steep fall in PDR is observed while comparing with 50 nodes in the same scenario, it continued till 100 nodes as shown in Figure 5.33.

On comparison with Figures 5.30 to 5.33, it is found that PDR is better with

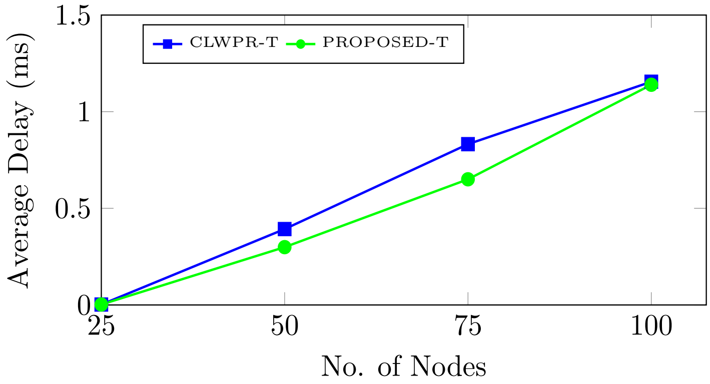


Figure. 5.38: AD on simulator generated mobility (Two-ray ground model)

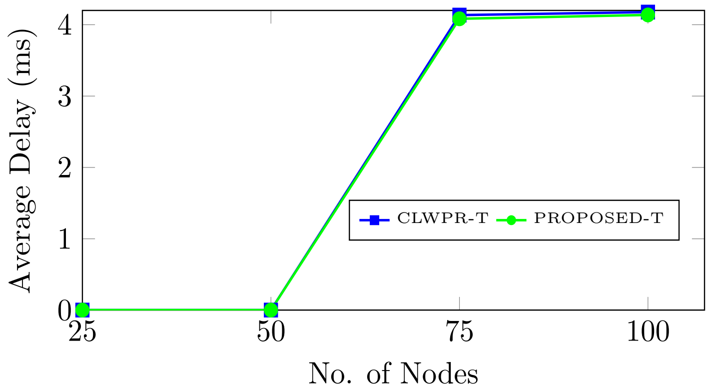


Figure. 5.39: AD on real GPS traces (Two-ray ground model)

Winner-II model compared to Two-ray ground model with simulator generated mobility, while with real GPS traces on both the propagation model up to 50 nodes PDR is stable, after that a sharp fall is recorded in PDR. With context to KF based prediction, it improves the PDR with Winner-II model on simulator generated mobility, while marginal improvement can be seen with other scenarios with the higher number of nodes.

5.5.2.2 Throughput

It measures the average number of bits received per second by each node. Figures 5.34 and 5.35 show the throughput on Two-ray ground model, while Figures 5.36 and 5.37 show throughput on Winner-II model for simulator generated traces and real GPS traces, respectively. From Figure 5.34, it is noticed that

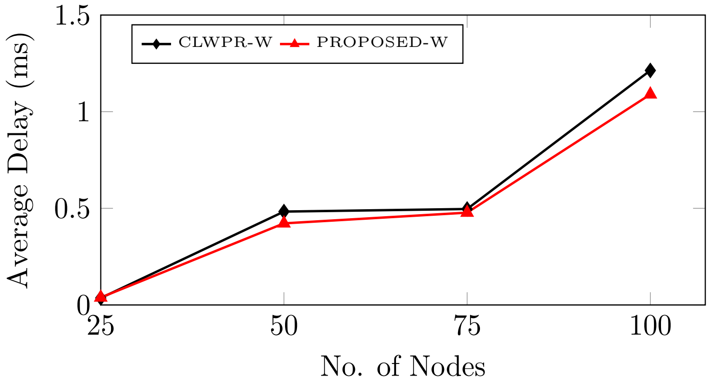


Figure. 5.40: AD on simulator generated mobility (Winner-II model)

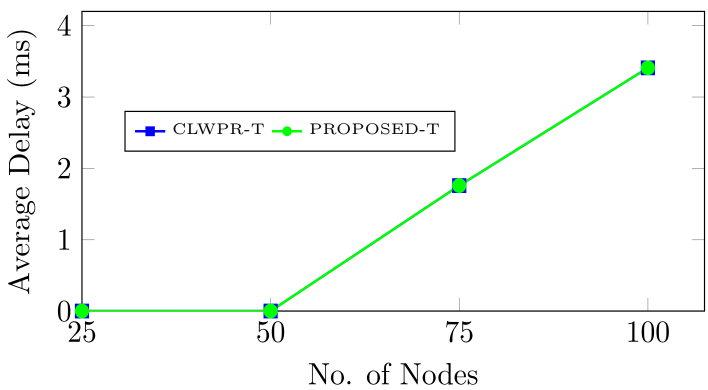


Figure. 5.41: AD on real GPS traces (Winner-II model)

PROPOSED-T have less throughput compared to CLWPR-T in all the scenarios. With 25 nodes CLWPR-T and PROPOSED-T has 125.68 kbps and 124.39 kbps throughput, respectively and it decreases to 49.272 kbps and 49.083 kbps for 100 nodes with respect to Two-ray ground model. On the other hand, it remains constant up to 50 nodes with real GPS traces after that throughput collapses to 31.909 kbps and 31.80 kbps with 75 nodes for CLWPR-T and PROPOSED-T, respectively, while with 100 nodes it dips to 24.37 kbps and 24.37 in the same order. On comparison with Figures 5.34 and 5.35, it is found that throughput is stable with simulator generated mobility compared to real GPS traces.

With reference to simulator generated mobility with Winner-II model, PROPOSED-W does better compared to CLWPR-W in all the scenario. 92.7943 kbps and 95.251 kbps are the maximum throughput with 25 nodes for CLWPR-W and PROPOSED-W, respectively. While 30.79 kbps and 33.16 kbps are the minimum throughput with 100 nodes for CLWPR-W and PROPOSED-W. From the results as shown in Figure 5.36, PROPOSED-W has better throughput compared to CLWPR-W.

With reference to real GPS traces with Winner-II model, PROPOSED-W and CLWPR-W both have equal throughput compared to simulator generated mobility and it has 127.94 kbps maximum throughput with up to 50 nodes, while it decreases to 27.92 kbps for 100 nodes for CLWPR-W and 27.93 for PROPOSED-W. In both the cases either on simulator generated traces or real GPS traces, only former scenario gives more throughput using KF based prediction, while it remains same with the latter case as shown in Figure 5.37.

On comparison with Figures 5.34 to 5.37, it is found that the PROPOSED-W has the highest throughput on simulator generated mobility compared to real GPS traces on Winner-II model using KF based prediction. With real GPS traces on both the propagation model up to 50 nodes throughput is stable and a sharp fall in throughput is observed with 75 and 100 nodes. With context to KF based prediction, it improves the throughput with Winner-II model on simulator generated mobility.

5.5.2.3 AD

Figures 5.38 and 5.39 show the average delay on Two-ray ground model. From Figure 5.38, CLWPR-T and PROPOSED-T has similar delay of 0.0022 ms with 25 nodes, while PROPOSED-T improves the delay as the number of nodes increases. With reference to simulator generated mobility PROPOSED-T has less delay compared to CLWPR-T. 0.0022 ms is the minimum delay in both the protocol, while 1.15 ms and 1.13 ms are the maximum delay in the dense network for CLWPR-T and PROPOSED-T, respectively. With reference to real GPS traces, CLWPR-T and PROPOSED-T has the similar delay up to 50 nodes. Average delay rose to 4.13 ms and 4.08 ms for 75 nodes for CLWPR-T and PROPOSED-T, respectively, while with 100 nodes it is 4.17 ms and 4.13

ms in the same order. Overall, location prediction minimizes average delay with Two-ray ground in all scenarios with simulator generated mobility, while marginal improvements can be seen with real GPS traces as shown in Figure 5.39.

Figures 5.40 and 5.41 show the delay performance with reference to Winner-II model, PROPOSED-W has 9.03% less delay compared to CLWPR-W in all the scenarios. 0.035 ms and 0.038 ms are the minimum observed delay in the sparse network for CLWPR-W and PROPOSED-W. However, PROPOSED-W has less delay compared to CLWPR-W in 50, 75 and 100 nodes. The maximum delay observed is 1.213 ms with CLWPR-W for 100 nodes while it is 1.08 ms with PROPOSED-W with simulator generated mobility.

The average delay with respect to real GPS traces is common for PROPOSED-W and CLWPR-W. Overall, in both the propagation model prediction based routing protocol using KF minimizes the delay by 11.4% on an average in 500m transmission range on simulator generated mobility, while with real GPS traces, KF based prediction and non KF based prediction routing protocol have the similar delay. From the results, it is evident that KF based prediction based position-based routing protocols minimizes the delay compared to other prediction models.

5.6 SUMMARY

With Respect to Model Based Mobility Traces

In routing high precision in location prediction is not desired as compared to other application such as automatic parking and cooperative driving our experimental results validated this statement. Based on these observations, it is concluded that the KF and EKF based prediction produce the same routing performance, however, EKF increases the running time to complete the simulation compared to KF due to involvement of additional computational steps such as computation of Jacobian. However, with respect to routing performance, it is observed that PROPOSED-500 has fair and consistent PDR compared to CLWPR, unlike PROPOSED-250. The throughput of the proposed protocol is better with

PROPOSED-500 in all scenarios, though it is noticed that the PROPOSED-250 shrinks the throughput with Two-ray ground model. Overall, location prediction enhances the throughput. It is also found that prediction minimizes the AD compared to CLWPR in both the protocol viz. PROPOSED-250 and PROPOSED-500. On comparison with heterogeneous and homogeneous traffic environments, it is found that the PDR, throughput and AD are almost similar in both the environments. Based on these observations, intuitively it is said that traffic environment does not affect the location prediction. On comparison with city and highway performance, it is found that the city has stable performance compared to highway whereas it should be reciprocal, however, vehicle deployment and location do affect the routing performance.

Based on the results it is said that the location prediction using KF and EKF in position-based routing protocol improves PDR, AD and throughput irrespective of traffic environment and propagation model.

With Respect to Real Time Mobility Traces

Based on our simulation results, it is observed that the prediction based position-based routing protocol using KF improves the performance. In 500m range, it gives better PDR, throughput and average delay compared to CLWPR on Winner-II model using simulator generated mobility compared to real GPS traces. With respect to Two-ray ground model, it is also noticed that the average delay is improved compared to CLWPR except PDR and throughput which remains almost same with simulator generated mobility.

On a comparison between Two-ray and Winner-II model results of the real GPS traces, it is found that the PDR, throughput and average delay are almost similar in proposed routing protocol with CLWPR in both the propagation model. Based on these observations, intuitively it is said that prediction does not improve routing performance with real GPS traces on NS-3.23 network simulator compared to CLWPR in the city. However, in this experiment, only GPS traces are taken from real time while remaining parameters are simulation based.

Overall, based on our simulation results including real GPS traces and simulator generated mobility it is evident that the prediction based routing protocol using KF improves routing performance by minimizing the average delay and enhancing the PDR and throughput compared to CLWPR with Winner-II model for 500m transmission range.

From the perspective of real time implementation, inclusion of KF into vehicle which rely on greedy forwarding can be used as a noise remover from the location. However, KF marginally increases the routing performance while EKF can be used where location precision is more important such as automatic parking and self driving car.

Related Publications

- Raj K Jaiswal, Jaidhar C D **EDAGF: Estimation & Direction Aware Greedy Forwarding for Urban Scenario in Vehicular Ad hoc Network** 15th IEEE International Conference on Scalable Computing and Communications (ScalCom 2015), Pages 814-821, Aug 10-14 2015,**Beijing, China**.

- Raj K. Jaiswal and Jaidhar C. D. **PPRP: Predicted Position-Based Routing Protocol Using Kalman Filter for Vehicular Ad Hoc Network**. In Proceedings of the 18th International Conference on Distributed Computing and Networking (ICDCN '17). ACM, New York, NY, USA, Article 23, 8 pages. DOI: https://doi.org/10.1145/3007748.3007762.

- Raj K Jaiswal, Jaidhar C D **A performance evaluation of Location Prediction Position-based Routing using Real GPS Traces for VANET** Wireless Personal Communications, Springer DOI:https://doi.org/10.1007/s11277-018-5839-6.

Chapter 6

Conclusion and Future Work

VANET is emerging as a promising paradigm in road transportation which aims to curb roadside accidents, fuel consumption and day-to-day traffic choke by giving a prior alert. VANET characteristics are similar to MANET such as multihop routing and self configuring node. Thus, many of the routing protocols developed for MANET are being used in VANET. In spite of the fact that duo have some common attributes yet MANET and VANET are divergent at some perspective such as intermittent network, high speed, mobility and power restriction. Thus, uses of MANET routing protocols in VANET is subject to the constraint. Though many researchers have evaluated the applicability of the topology based routing protocols in VANET, nevertheless, at the outset, it is observed that some of the aspects missed out in previous works. Thus, Chapter 3 re-evaluates the applicability of AODV and OLSR protocols from a different perspective and concludes the work as follows:

Based on simulation results, it is found that AODV and OLSR routing protocols do not have stable PDR and throughput with respect to vehicle density and data generation rate. It is found that the routing overhead and average delay increases with the vehicle density and decreases when data generation rate increases. It is also observed that the single crossroad performance is better compared to multiple crossroad. Hence, it is concluded that the based on single crossroad performance applicability of MANET routing protocols in VANET can not be decided due to inappropriate parameters. Additionally, performance with constant speed is better than variable speed as it does not affect the topology compared to real scenarios. Thus, based on obtained results for the entire city road network scenario, AODV and OLSR protocols are not feasible to be used in VANET as endurance of the routing protocols with varying vehicle density and data generation rate are not satisfactory with VANET characteristics. However, further AODV and OLSR protocols performance can be evaluated as a future work as follows:

- Both the protocols should be re-evaluated on same parameters as explained in Chapter 3 by replacing the Two-ray ground propagation model with nakagami and Winner-II models.

- Simulation should be carried out only using multiple crossroad scenarios.

However, position-based routing protocols are more appropriate to be used in VANET as they do not maintain network topology, rather they uses GPS position as a *location_id* during routing. However, GPS locations also have an error due to various reasons such as trees, buildings and environmental effect. Thus, due to this error, vehicle GPS position will be different from the real location. It is also found that due to error, GPS location will be 05-100m apart from the real location which certainly effects the performance of the many application used in VANET such as automatic parking, cooperative driving and routing. Thus, in this thesis, Chapter 4 proposed a location prediction algorithm based on EKF to predict the vehicle location by minimizing error in it. To evaluate the efficacy of the prediction model various set of experiments carried out. Based on their results, following observations are made with respect to location prediction model:

It is observed that location prediction using EKF for model based traces is almost equal to the measured location. However, a coordinate system in model based traces is different from the GPS system. It is also observed in our simulation results that the performance of the prediction algorithm is better on the highway compared to the city scenario.

With reference to the real traces, EKF prediction algorithm performs better on the highway compared to the city. However, it is lower than the model based traces. Nevertheless, model based traces are unrealistic to be used in real world scenarios, unlike real traces. In addition, DE is less on the highway with real and model based traces compared to the city. On comparison of DE between model and real based traces, it is found that the model based traces showed less error compared to the real traces. Velocity error is less with reference to model based traces on the highway compared to the real traces.

On the basis of DE, RMSE, AEDE and VE results, it is also observed that the EKF based prediction outperforms the KF based prediction. Hence, it is concluded that the EKF based prediction should be used in VANET where location precision is more crucial, compared to KF based prediction. Further, following suggestions can be taken as future work:

- To use KF and EKF based prediction module in position-based routing protocol in VANET.
- The performance of EKF should be evaluated with other VANET application where high precision in location prediction is a prime concern such as self driving car and automatic car parking.
- The performance of KF and EKF based prediction module should be compared with machine learning approach.
- Mathematical computation of EKF time complexity is another area for future exploration.

Based on the recommendations of Chapter 4 a KF and EKF based prediction modules are devised in Chapter 5 to be used in position-based routing protocol. Based on the experimental results following observations are made:

In experiments, it is found that the KF and EKF based prediction produce the same routing performance as in routing protocol location precision is not that much required how it is needed in other applications as showed in Table 1.1 of Chapter 1. In addition, EKF takes more time to complete the simulation compared to KF due to additional computational steps such as computation of Jacobian. However, with respect to routing performance, it is observed that PROPOSED-500 has fair and consistent PDR compared to CLWPR, unlike PROPOSED-250. The throughput of the protocol is better with PROPOSED-500 in all scenarios, though it is noticed that the PROPOSED-250 shrinks the throughput with Two-ray ground model. Overall, prediction enhances the throughput. It is also found that prediction minimizes the AD compared to CLWPR in both the protocol viz. PROPOSED-250 and PROPOSED-500. On comparison with heterogeneous and homogeneous traffic environments, it is found that the PDR, throughput and AD are almost similar in both the environments. Based on these observations, intuitively it is said that traffic environment does not affect the prediction. On comparison with city and highway performance, it is found that the city has stable performance compared to highway scenario, whereas it should be reciprocal, however, vehicle deployment and location do affect the routing performance.

Based on the results it is said that the location prediction using KF and EKF in position-based routing improves PDR, AD and throughput irrespective of traffic environment and propagation model. This work suggests the following future work, to evaluate the efficacy of the prediction module.

- The KF and EKF prediction module performance must be evaluated on real-time GPS traces.

Based on the recommendation of Chapter 5, Section 5.5 evaluates the prediction based position-based routing performance on real-time GPS traces. Based on simulation results following conclusions are made.

It is observed that the prediction based position-based routing protocol using KF improves the performance. In 500m range, it gives better PDR, throughput and average delay compared to CLWPR on Winner-II model using simulator generated mobility compared to real GPS traces. With respect to Two-ray ground model, it is also noticed that the average delay is improved compared to CLWPR except PDR and throughput which remains almost same with simulator generated mobility.

On a comparison between Two-ray ground and Winner-II model results of the real GPS traces, it is found that the PDR, throughput and average delay are almost similar in proposed routing protocol with CLWPR in both the propagation model. Based on these observations, intuitively it is said that prediction does not improve routing performance with real GPS traces on NS-3.23 network simulator compared to CLWPR in the city. However, in this experiment, only GPS traces are taken from the real time while remaining parameters are simulation based. Thus, evaluation of the prediction based position-based protocol using KF with real time environment is seen as a future work.

Overall, based on our simulation results including real GPS traces and simulator generated mobility it is evident that the prediction based routing protocol using KF improves routing performance by minimizing the average delay and enhancing the PDR and throughput compared to CLWPR with Winner-II model for 500m transmission range.

Appendix I

Location of the Vehicle using Advance Prediction

Time(S)	Real-X	Real-Y	Pre-X	Pre-Y	DE	Diff. in X	Diff. in Y
1	220.8783553757	23.000001	222.530073353	23.0004616298	1.6517180415	1.6517179773	0.0004606298
2	225.6608541899	23.000001	228.0744342861	23.0004617038	2.4135801402	2.4135800962	0.0004607038
3	230.5411367521	23.000001	233.6011636966	23.0004617148	3.0600269792	3.0600269445	0.0004607148
4	235.4768525653	23.000001	239.1103325644	23.0004617258	3.6334800283	3.6334799991	0.0004607258
5	240.4428349652	23.000001	244.6019943826	23.0004617367	4.1591594429	4.1591594174	0.0004607367
6	245.4249800027	23.000001	250.0761947821	23.0004617476	4.6512148022	4.6512147794	0.0004607476
7	250.4156494357	23.000001	255.5329946041	23.0004617585	5.1173451891	5.1173451684	0.0004607585
8	255.4107850261	23.000001	260.9724394794	23.0004617694	5.5616544723	5.5616544533	0.0004607694
9	260.4082521826	23.000001	266.3946054596	23.0004617802	5.9863532947	5.986353277	0.0004607802
10	265.4069342494	23.000001	271.7995229651	23.0004617909	6.3925887323	6.3925887157	0.0004607909
11	270.4062486843	23.000001	277.1872832579	23.0004618017	6.7810345893	6.7810345736	0.0004608017
12	275.405891876	23.000001	282.5579167584	23.0004618124	7.1520248973	7.1520248824	0.0004608124
13	280.405706431	23.000001	287.9114843078	23.000461823	7.5057778909	7.5057778768	0.000460823
14	285.4056099274	23.000001	293.2480467474	23.0004618337	7.8424368336	7.84243682	0.0004608337
15	290.4055595242	23.000001	298.5676344977	23.0004618443	8.1620749865	8.1620749735	0.0004608443

16	295.4055333354	23.000001	303.8703084	23.0004618548	8.4647750771	8.4647750646	0.0004608548
17	300.4055197195	23.000001	309.1561292953	23.0004618654	8.750609588	8.7506095758	0.0004608654
18	305.4055126228	23.000001	314.4251580248	23.0004618759	9.0196454138	9.019645402	0.0004608759
19	310.4055087857	23.000001	319.6774554298	23.0004618863	9.2719466555	9.2719466441	0.0004608863
20	315.4055068113	23.000001	324.9130519309	23.0004618968	9.5075451307	9.5075451196	0.0004608968
21	320.4055057682	23.000001	330.1320083691	23.0004619072	9.7265026118	9.7265026009	0.0004609072
22	325.4055051908	23.000001	335.3343855858	23.0004619175	9.9288804057	9.928880395	0.0004609175
23	330.4055050791	23.000001	340.5202140014	23.0004619279	10.1147089328	10.1147089223	0.0004609279
24	335.4055049673	23.000001	345.6895544572	23.0004619382	10.2840495002	10.2840494899	0.0004609382
25	340.4055048556	23.000001	350.8424677943	23.0004619484	10.4369629489	10.4369629387	0.0004609484
26	345.4055047438	23.000001	355.979014854	23.0004619587	10.5735101203	10.5735101102	0.0004609587
27	350.405504632	23.000001	361.0992260567	23.0004619689	10.6937214346	10.6937214247	0.0004609689
28	355.4055045203	23.000001	366.2031622438	23.000461979	10.7976577334	10.7976577235	0.000460979
29	360.4055044085	23.000001	371.2908842564	23.0004619892	10.8853798576	10.8853798479	0.0004609892
30	365.4055042968	23.000001	376.3624529356	23.0004619993	10.9569486485	10.9569486388	0.0004609993
31	370.405504185	23.000001	381.417898702	23.0004620093	11.0123945266	11.012394517	0.0004610093
32	375.4055040732	23.000001	386.4572823969	23.0004620194	11.0517783333	11.0517783237	0.0004610194
33	380.4055039615	23.000001	391.4806344407	23.0004620294	11.0751304888	11.0751304792	0.0004610294
34	385.4055038497	23.000001	396.4880156748	23.0004620394	11.0825118347	11.0825118251	0.0004610394
35	390.405503738	23.000001	401.4794869403	23.0004620493	11.0739832119	11.0739832023	0.0004610493
36	395.4055036262	23.000001	406.4551090783	23.0004620592	11.0496054617	11.0496054521	0.0004610592
37	400.4055035144	23.000001	411.4149125094	23.0004620691	11.0094090046	11.009408995	0.0004610691

38	405.4055034027	23.000001	416.3589580749	23.000462079	10.9534546819	10.9534546722	0.000461079
39	410.4055032909	23.000001	421.2872761953	23.0004620888	10.8817729141	10.8817729044	0.0004610888
40	415.4055031792	23.000001	426.1999277118	23.0004620986	10.7944245425	10.7944245326	0.0004610986
41	420.4055030674	23.000001	431.0969734656	23.0004621083	10.6914704081	10.6914703982	0.0004611083
42	425.4055029557	23.000001	435.9784742978	23.0004621181	10.5729713522	10.5729713421	0.0004611181
43	430.4055028439	23.000001	440.8444606291	23.0004621278	10.4389577954	10.4389577852	0.0004611278
44	435.4055027321	23.000001	445.69496288	23.0004621374	10.2894601582	10.2894601479	0.0004611374
45	440.4055026204	23.000001	450.5300723123	23.0004621471	10.1245697024	10.1245696919	0.0004611471
46	445.4055025086	23.000001	455.349788926	23.0004621567	9.9442864281	9.9442864174	0.0004611567
47	450.4055023969	23.000001	460.1542039829	23.0004621662	9.7487015969	9.748701586	0.0004611662
48	455.4055022851	23.000001	464.9433479036	23.0004621758	9.5378456296	9.5378456185	0.0004611758
49	460.4055021733	23.000001	469.7172815292	23.0004621853	9.3117793673	9.3117793559	0.0004611853
50	465.4055020616	23.000001	474.4760352804	23.0004621948	9.0705332305	9.0705332188	0.0004611948
51	470.4055019498	23.000001	479.2196699982	23.0004622042	8.8141680604	8.8141680484	0.0004612042
52	475.4055018381	23.000001	483.9482161034	23.0004622136	8.5427142778	8.5427142653	0.0004612136
53	480.4055017263	23.000001	488.6617344371	23.000462223	8.2562327237	8.2562327108	0.000461223
54	485.4055016146	23.000001	493.3602858404	23.0004622324	7.9547842392	7.9547842259	0.0004612324
55	490.4055015028	23.000001	498.043900734	23.0004622417	7.6383992451	7.6383992312	0.0004612417
56	495.405501391	23.000001	502.7126399591	23.000462251	7.3071385826	7.3071385681	0.000461251
57	500.4055012793	23.000001	507.3665339362	23.0004622603	6.9610326722	6.9610326569	0.0004612603
58	505.4055011675	23.000001	512.005673927	23.0004622695	6.6001727756	6.6001727595	0.0004612695
59	510.4055010558	23.000001	516.6300295111	23.0004622788	6.2245284724	6.2245284553	0.0004612788

60	515.405500944	23.000001	521.2396615296	23.0004622879	5.8341606038	5.8341605856	0.0004612879
61	520.4055008322	23.000001	525.8346916648	23.0004622971	5.4291908522	5.4291908326	0.0004612971
62	525.4055007205	23.000001	530.4151199167	23.0004623062	5.0096192175	5.0096191962	0.0004613062
63	530.4055006087	23.000001	534.9809462855	23.0004623153	4.5754457	4.5754456768	0.0004613153
64	535.405500497	23.000001	539.5322924533	23.0004623244	4.1267919821	4.1267919563	0.0004613244
65	540.4055003852	23.000001	544.0691584202	23.0004623334	3.663658064	3.663658035	0.0004613334
66	545.4055002734	23.000001	548.5916050275	23.0004623424	3.1861047875	3.1861047541	0.0004613424
67	550.4055001617	23.000001	553.0996931162	23.0004623514	2.694192994	2.6941929545	0.0004613514
68	555.4055000499	23.000001	557.5934226863	23.0004623604	2.187922685	2.1879226364	0.0004613604
69	560.4054999382	23.000001	562.0729154203	23.0004623693	1.667415546	1.6674154821	0.0004613693
70	565.4054998264	23.000001	566.5381713182	23.0004623782	1.1326715858	1.1326714918	0.0004613782
71	570.4054997147	23.000001	570.9891903798	23.0004623871	0.5836908475	0.5836906651	0.0004613871
72	575.4054996029	23.000001	575.4260942877	23.0004623959	0.0205998526	0.0205946848	0.0004613959
73	580.4054994911	23.000001	579.8488830417	23.0004624047	0.5566166407	0.5566164494	0.0004614047
74	585.4054993794	23.000001	584.2576174831	23.0004624135	1.147881989	1.1478818963	0.0004614135
75	590.4054992676	23.000001	588.6523584531	23.0004624223	1.7531408752	1.7531408145	0.0004614223
76	595.4054991559	23.000001	593.0331059516	23.000462431	2.3723932491	2.3723932043	0.000461431
77	600.4054990441	23.000001	597.3999208199	23.0004624397	3.0055782596	3.0055782242	0.0004614397
78	605.4054989323	23.000001	601.7528638991	23.0004624484	3.6526350624	3.6526350332	0.0004614484

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