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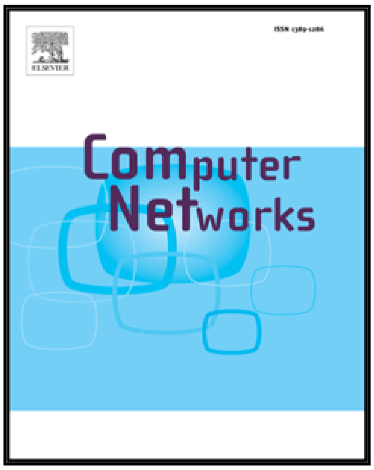

Prediction-based Protocols for Vehicular Ad Hoc Networks: Survey and Taxonomy

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PII: S1389-1286(17)30392-4
DOI: 10.1016/j.comnet.2017.10.009
Reference: COMPNW 6324

To appear in: *Computer Networks*

Received date: 9 August 2017
Revised date: 24 October 2017
Accepted date: 29 October 2017

Please cite this article as: Islam Tharwat Abdel-Halim , Hossam Mahmoud Ahmed Fahmy , Prediction-based Protocols for Vehicular Ad Hoc Networks: Survey and Taxonomy, *Computer Networks* (2017), doi: 10.1016/j.comnet.2017.10.009

00 (2017) 000–000

Available online at www.sciencedirect.com

Journal homepage:

Review Article

Prediction-based Protocols for Vehicular Ad Hoc Networks: Survey and Taxonomy

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ARTICLE INFO

Article history:
Received 00 December 00
Received in revised form 00 January 00
Accepted 00 February 00

Keywords:
Prediction
Movement
VANET
Survey
Taxonomy

ABSTRACT

The high mobility of vehicles as a major characteristic of Vehicular Ad Hoc Networks (VANETs) affects vividly the dynamic nature of the networks and results in additional overhead in terms of extra messages and time delay. The future movements of the vehicles are usually predictable. The predictability of the vehicles future movements is a result of the traffic conditions, the urban layout, and the driving requirements to observe the traffic constrains. Hence, predicting these future movements could play a considerable role for both building reliable vehicular communication protocols and solving several issues of intelligent transportation systems. In the literature, numerous prediction-based protocols are presented for VANETs. Therefore, this paper follows the guidelines of systematic literature reviews to provide a premier and unbiased survey of the existing prediction-based protocols and develop novel taxonomies of those protocols based on their main prediction applications and objectives. A discussion on each category of both taxonomies is presented, with a focus on the requirements, constrains, and challenges. Moreover, usage analysis and performance comparisons are investigated in order to derive the suitability of each prediction objective to the various applications. Also, the relevant challenges and open research areas are identified to guide the potential new directions of prediction-based research in VANETs. Throughout this paper, information is provided to developers and researchers to grasp the major contributions and challenges of the predictive protocols in order to pave the way for enhancing their reliability and robustness in VANETs.

1. Introduction

Vehicular Ad Hoc Networks (VANETs) is a subclass of Mobile Ad Hoc Networks (MANETs) and the general characteristics of VANETs are typically inherited from MANETs in terms of lack of infrastructure, self-management and shared transmission media [1]. However, VANETs exhibit plenty of unique characteristics and operate in a challenging communications environment, which create diverse considerable challenges to develop efficient vehicular communication protocols [2]. For instance, the high speed of the vehicles and the large scale of the network lead to dynamic topology.

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Peer review under responsibility of xxxxx.

Hosting by Elsevier

http://dx.doi.org/10.1016/j.aebj.2014.10.012

Consequently, the rapid and continuous changing topology causes frequent disconnections of the communication links, which results in an increased overhead of the communication protocols [3].

From another perspective, the future movements of the vehicles in VANETs are predictable due to the constraints of urban layout, road geometry, and traffic conditions [4-5]. Hence, accurate prediction of the vehicles future movements could play a crucial role for both building efficient vehicular communication protocols and enhancing the vehicular transportation systems. Predicting the vehicles future movements is defined as "the estimation of their future locations, trajectories and the time required to reach their destinations", which requires precise analysis of their mobility characteristics [6].

In the literature, numerous prediction-based protocols were proposed to improve the efficiency, reliability and robustness of vehicular communication networks. Fig. 1 shows the number of publications between 2006 and 2016 in relevant scientific sources (IEEE, ACM, Springer, and Science Direct). As shown, the noticeable increase of the number of publications in the last decade emphasize the importance of studying the various prediction objectives and applications of those protocols

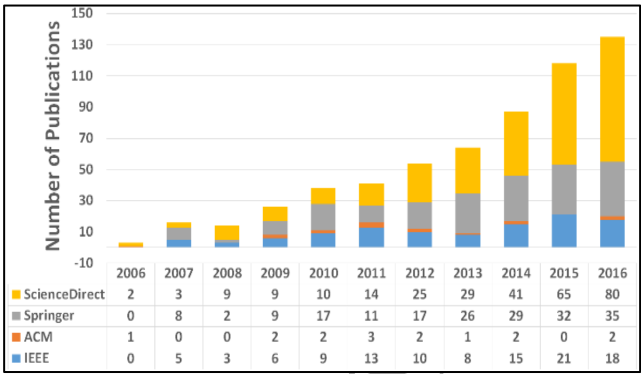


Fig. 1. The number of publications of prediction-based protocols for VANETs in relevant scientific sources over the period 2006-2016.

The predictive protocols are used in different aspects of VANETs such as routing, traffic management, data forwarding, and road safety. However, until now no overviews of the existing predictive protocols have been presented to sum up the best available researches. To the best of our knowledge, this paper is premier to survey the most recent research progress of the predictive protocols in VANETs. The main contributions of this survey paper are: 1) Developing a clear taxonomy of the predictive protocols according to their main applications and prediction objectives, 2) Deducing the suitability of each prediction objective to the different applications, and 3) Addressing the related challenges and the open research areas.

The rest of this paper is structured as follows. Section 2 discusses the research methodology. Section 3 gives an overview of VANETs. The main applications of the predictive protocols are discussed in Section 4. A taxonomy based on the prediction objective and a comprehensive survey of the predictive protocols in VANETs are given in Section 5. Section 6 gives the usage analysis, performance comparisons, and relevant challenges of the predictive protocols before summing up the paper with a conclusion in Section 7.

2. Research Methodology

This section aims to present the process adopted to perform a comprehensive and unbiased survey of the predictive protocols in VANETs. Generally, the survey papers might suffer from several shortcomings such as the unclear and inconsistent research questions being posed, the lack of clear organizational structure, and the inability to discriminate between relevant and irrelevant materials. In this context, the guidelines of systematic literature reviews laid by Kitchenham [7] were introduced to ensure the reliability and integrity of the review articles. Therefore, we customized those guidelines, with a focus on the following research questions in order to be better suited for the objectives and the purposes of this survey:

1) What are the prediction objectives of the proposed protocols?
2) Which applications can benefit from the use of prediction in VANETs?
3) What are the criteria of evaluating and comparing the performance of the proposed protocols?
4) What are the existing related challenges and open research areas?

The stages involved in performing this survey are as following; initially, identification of resources and selection of studies; then finally, data extraction and synthesis. The following subsections give an overview of each stage.

2.1. Identification of Resources and Selection of Studies

The improper identification of the reviewed articles might lead to inconsistent and inaccurate conclusions. Therefore, recognizing the relevant keywords plays a pivotal role in identifying the proper resources. Thus, an extensive search using (Document Title: ("Vehicular" OR "VANET") AND "Prediction") as a query text is conducted within the most prominent scientific digital libraries (IEEE, ACM, Springer, and Science Direct).

The search is filtered to show only the articles that were written in English and published between 2006 and 2016 in a reliable peer-reviewed journal or conference. As a result, a total of 596 articles had been found. These articles were stored in the INITIAL LIST.

In order to select the relevant studies, we excluded the duplicate articles or the articles that were not clearly related to the research questions. Then, the remaining articles were subjected to a quality screening such that the articles were scored according to the following quality criteria:

- The clearness of the research aim.
- The feasibility of the proposed protocol.
- The clarity of results.
- The overall quality of writing.

All the articles were examined by assigning High/Medium/Low to specify either each criterion was met or not. Then, a score for each articles was calculated by giving one point for each "High", 0.5 points for each "Medium", and zero points for each "Low" the article that achieved a score less than 2 points is excluded from the *FINAL LIST* used in our survey.

Based on our exclusion criteria, 57 articles were selected and stored in the *FINAL LIST*. All results and discussions provided in this work were extracted from the studies included in the *FINAL LIST*.

2.2. Data Extraction and Synthesis

In this survey, the data extracted from each article in the *FINAL LIST* were the source (journal or conference), year of publication, full reference, author's information, the technical part related to the prediction model/algorithm/protocol that was addressed in the article, performance metrics, results and conclusion.

The extracted data was analyzed as per the used terminologies, methods and objectives to categorize the articles in the *FINAL LIST*.

3. Overview of VANETs

Without a doubt, extensive literature is already available in order to provide brief background for VANETs. However, for the reader's convenience, this section aims to provide background knowledge to realize the overall architecture of VANETs and cover its related characteristics, challenges, and mobility models. Further, we present simple scenarios to better understand the possibility of improving the vehicular communication protocols by utilizing the predictive information of the vehicles future movements.

3.1. Architecture of VANETs

VANETs follow the same communication and architecture principles of MANETs in terms of the self-management, self-origination and shared radio [8]. Communication in VANETs can be classified though into two main classes: 1) Vehicle to Vehicle communication (V2V), where the vehicles can communicate directly to each other; and 2) Vehicle to Infrastructure communication (V2I), where the vehicle can communicate with immovable equipment by the side of the roads.

Roadside Unit (RSU), On Board Unit (OBU) and Application Unit (AU) are the cardinal components used for VANETs communication [9]. Usually, The RSU is fixed along the roads, while both OBU and AU are hosted within the vehicle. The RSU provides services to vehicles such as Internet connectivity, information broadcasting and safety applications. On the other hand, The OBU manages the network communication between vehicles and the RSUs. Moreover, the communication capabilities of the OBU allow the AU to get benefited from the provided services in the network.

3.2. Characteristics of VANETs

VANETs have several unique characteristics compared to standard MANETs. In what follows, the peerless characteristics of VANETs are listed [9-10]:

- *Movement prediction:* The movements of vehicles are constrained by the urban layout such as streets, intersections and roads, so that the future movements of the vehicles could be predictable.
- *Insignificant power limitations:* VANETs have no power limitations, as each vehicle is equipped with a long life battery.
- *Large-scale network:* The huge number of vehicles participating in the networks leads to a broad scale network, especially in dense urban areas such as the city center, the entrance of the big cities, and highways.
- *Mutable network density*: The variation of traffic flow causes mutable network density in VANETs, i.e. the network density could be very low such as the case of rural areas, or massive such as the case of rush hours or traffic jam.

3.3. Challenges of VANETs

Diverse applications are used in the Intelligent Transportation Systems (ITS), which range from traffic safety applications to infotainment ones. Such variety of applications introduces disparate requirements on the vehicular communication protocols. These contrasting requirements result in new challenges [8-11]:

- *Bandwidth limitations:* Due to the lack of centralized coordinator that manages the utilization of limited bandwidth and content operation, VANETs suffer from channel congestion, especially in a high-density area.
- *Delay constraints:* VANETs applications regularly have strict time policies. Therefore, providing acceptable time delay is vital for designing efficient vehicular communication protocols.
- *Privacy and accountability rights:* The tradeoff between privacy and accountability need to be handled in vehicular communication. Each vehicle has to trust the source of the information it receives. At the same time, the driver's privacy should be protected.
- *Cross-layering protocols:* Real-time and multimedia applications have strict constraints in terms of time and location. Owing to the dynamic topology, the routes are frequently altered. Thus, providing reliable connection through the transport layer is efficient in such situation. Therefore, the design of cross-layer protocols can be advantageous in VANETs.
- *Small effective diameter:* VANETs suffer from feeble connectivity between vehicles due to the small effective network diameter. Thus, it is inapplicable for each vehicle to preserve the entire topology of VANET; accordingly, the routing protocols suffer many hitches.
- *Security attacks:* Due to the openness nature of VANETs, it can be targeted by enormous number of attacks. Consequently, discovering the new attacks related to vehicular communication and securing the routing protocols against such types of attacks is a fateful issue.
- *High dynamic and frequently disconnected topology:* The network topology of VANETs tends to change frequently due to the vehicles high mobility. As a result, VANETs are subjected to various challenging situations of operation with intermittent connectivity, frequent link disruption and disconnection, as well as the repeated partitioning of the topology. Therefore, a new research paradigm named as Vehicular Delay Tolerant Networks (VDTNs) is introduced to cope with such situations.

3.4. Mobility Models for VANETs

Establishing a realistic mobility model for VANETs requires taking into consideration several constraints such as traffic status, street map structure, vehicle density and speed, inter-vehicle behavior in urban or topographical circumstances, and obstructions such as architectural structures and trees [6]. In the literature, couple categories of constraints were presented separately:

- *Macroscopic*: Include all the constraints that have an effect on the vehicles movement patterns such as trip generation, initial and destination positions, traffic signs, as well as overtaking and safety rules.
- *Microscopic*: Include all the constraints that are related to the individual behavior of the vehicles such as inter-vehicle interactions, traveling speed, as well as general driving attitude related to driver's age, sex or mood.

3.5. Prediction of Vehicles Movements in VANETs

The potential high speed of moving vehicles leads to frequently disconnected network, highly dynamic topology and different network density in VANETs [2]. Thence, the existing communication protocols that were designed for MANETs are not favorable in their current form for wireless vehicular communications [12]. Developing a convenient protocol for vehicular communication networks requires conscious realization for the characteristics and challenges of these networks.

Therefore, predicting the network's future topology could play a key role to enhance the ITS as well as the vehicular communications [13]. In VANETs, The vehicles movements show clear regularity compared to the nodes' movements in MANETs. For example, a vehicle travelling along a street will maintain its current speed toward a given direction for a certain period of time. On the other side, recent years have witnessed an increasing number of vehicles equipped with Global Positioning System GPS-enabled navigation systems, which allow the early and continuous knowledge about the future locations of vehicles and the movement information [14]. Additionally, identifying the vehicles mobility characteristics such as the current speed, location, and direction is pivotal to predict the network's future topology.

Fig. 2 illustrates the influence of the future movement prediction in the process of selecting the optimal relay vehicle in VANETs, where predicting the future movements of the neighboring vehicles may give the forwarding vehicle good visibility to select the optimal relay vehicle.

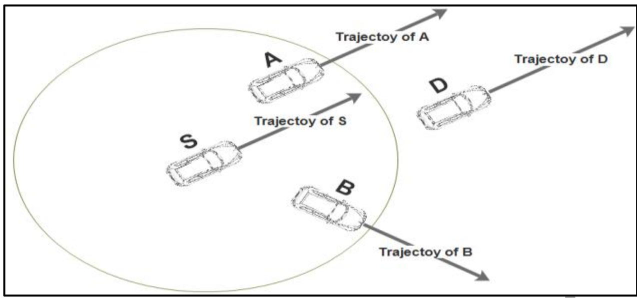


Fig. 2. Influence of predicting the future vehicles movements on the selection of the optimal relay vehicle.

Let *S* and *D* represent the source and destination vehicles respectively; while vehicles *A* and *B* are two potential relay vehicles. In contrast to vehicle *B*, which moves away from *S* and *D*, vehicle *A* moves in the same direction as *S* and *D*. Therefore, the communication link (*S*, *B*) is short-lived and has inferior expiration time compared to the communication link (*S*, *A*). Hence, if vehicle *S* takes into consideration the future movement of the potential relay vehicles, then vehicle *A* should be selected as the next hop. The mentioned example shows that the prediction capability to the vehicle future movement could improve the routing performance and reduce the communication overhead.

Another plain example that illustrates the exploitation of the trajectory-based coverage is given in Fig. 3. The figure shows three vehicles *A*, *B*, and *C*; both vehicles *B* and *C* carry a message to the target region. As shown, vehicle *C* can deliver the message directly; this is because the direct coverage of vehicle *C* overlaps the target region. On the other hand, vehicle *B* can deliver the message to the target region through vehicle *A* as they will encounter each other at 10:15 before vehicle *A* overlaps the target region. Obviously, the early knowledge of the vehicles future trajectories could improve the data forwarding and dissemination protocols in VANETs.

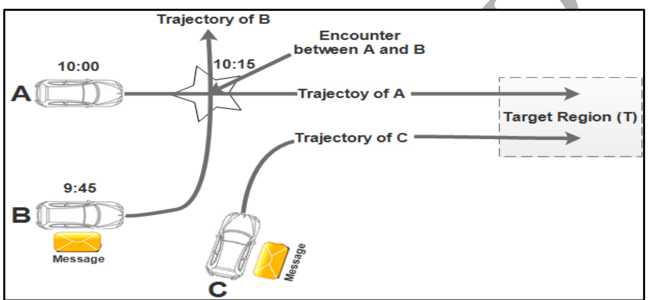


Fig.3 Example of exploiting trajectory-based coverage.

4. Taxonomy of Prediction-based Protocols in VANETs Based on their Applications

Prediction is used in several VANETs applications. In this article, we focus on the major applications where the prediction techniques are widely used. Identifying the various applications of the prediction-based protocols is a paramount, since the design of a prediction based protocol is habitually affected by its targeted application. As shown in Fig.4, the prediction-based protocols are classified in this paper according to their main application into five main categories: 1) Routing, 2) Data Forwarding, 3) Traffic Management, 4) Road Safety, and 5) General Purpose. Table 1 summarizes the discussed protocols in this survey, grouped by their main application. Additionally, the table shows the acronym used for each protocol in the rest of this paper.

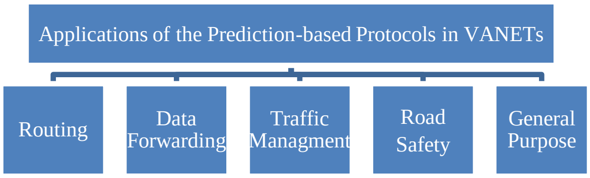


Figure 4. Applications of the prediction-based protocols in VANETs.

4.1. Routing

A route between source and destination is composed of several consecutive communication links between intermediate vehicles. Due to the highly dynamic nature of VANETs, existing communication links are repeatedly broken and new links are repeatedly established. A fundamental aim of the routing protocols is to select the most stable routes in order to increase the overall performance of the network and mitigate the necessity of reconstructing new routes frequently. Therefore, predicting the future state of the network is introduced as an effective mechanism to enhance various routing strategies in VANETs [15-19]. For instance, predicting the route lifetime allows routing protocols to select the most stable routes among all the available routes, which results in significant reduction in the number of route failures. Moreover, it grants a way to take preemptive actions to minimize the adverse effect of the route failure.

On the other hand, the position-based routing is introduced as a suitable solution for a highly dynamic environment such as VANETs, because it is a pathless routing and it maintains only the geographical location information of the neighbors instead of maintaining routing entries for the destinations. Based on the exchanged geographical information, a vehicle selects the relay vehicle that is the closest to the destination among all its neighbors. A significant subset of the predictive protocols aims to predict the accurate positions, velocities, and moving directions of the vehicles to enhance the performance of the position-based routing [20-32]. The predictive information of the vehicles is used in the relay vehicle selection process in order to increase the possibility of selecting the most stable relay vehicles.

Whereas the main objective of multicast/ geocast-based routing protocols is to deliver a message to a target group or geographical region in VANETs. Therefore, predicting the vehicle future location or trajectory is introduced to characterize the ability of vehicle to deliver a given message to the target vehicles [33-38].

4.2. Data Forwarding

Data forwarding protocols are proposed to cope with the large scale and frequent partitioning of the network, in which vehicles carry or forward messages progressively close to the destination by selecting the shortest potential path based on the trajectories of the vehicles. However, without a global knowledge of the network, a situation called the "local maximum" may occur, in which the forwarding vehicle has limited information about the future long-term locations of the destinations and the relay vehicles. For this reason, predicting the individual future trajectories of the vehicles is necessary to improve the efficiency of data forwarding protocols [39-46].

In a prevalent manner, predicting the future trajectory of a vehicle is accomplished by extracting the mobility patterns from historical traces, then analyzing the movements' regularity of individual vehicle as well as the traffic status.

4.3. Traffic Management

Traffic management plays a key role in many aspects of the ITS such as dynamic trip planning, route guidance, and traffic congestion avoidance. In view of practicality, the accurate prediction of the vehicle travel time will provide commuters with valuable information to decide whether or not to make necessary changes to their departure times or future routes. Moreover, infotainment solutions are developed in VANETs in order to allow the users on board of vehicles to plan, deploy, and receive information and infotainment relevant to the services available in their considered area.

Therefore, several travel time prediction algorithms have been proposed [47-52] with various applied techniques to predict the travel time, such as time series data analysis, linear regressing model, historical trend extrapolation, Kalman filter, and artificial neural network. Furthermore, predictive road traffic management systems are proposed in order to predict traffic congestions, future traffic intensities, and average-speed of vehicles [53-57].

4.4. Road Safety

VANETs are attracting an increasing attention to improve road safety through the dissemination of traffic related information to relevant vehicles. Therefore, predicting vehicle motion/location, driver behavior and road geometry are widely used to provide vehicles with driving assistance or generate an accurate warning in a timely fashion regarding a dangerous situation ahead [58-64].

Table 1: List of the prediction-based protocols in this survey grouped by their main application

Application		Protocol Name	Acronym	Citation
Routing	Reactive Routing	Prediction Based Routing	PBR	[15]
		A Mobility-Aware Link Enhancement Mechanism for Vehicular Ad Hoc Networks	MAODV-P/PF	[16]
		Profile Based Routing in Vehicular Ad Hoc Networks	Profile-BR	[17]
		A Novel Vehicular Location Prediction Based on Mobility Patterns for Routing in Urban VANET	PSR	[18]
		Mobility State Based Routing Method in Vehicular Ad Hoc Network	MSBR	[19]
	Position/Location based Routing	A Prediction Based Routing Algorithm for Vehicular Ad Hoc Networks	LPRV	[20]
		An Anchor-Geography Based Routing Protocol with Mobility Prediction for VANET in City Scenarios	AGP	[21]
		Reliable Freestanding Position Based Routing in Highway Scenarios	FPBR	[22]
		Movement Based Routing Algorithm	MORA	[23]
		Geographic Routing Based on Predictive Locations in Vehicular Ad Hoc Networks	GRPL	[24]
		A Movement Prediction Based Joint Routing and Hierarchical Location Service for VANET	PHRHLS	[25]
		Movement Prediction Based Routing	MOPR	[26]
		Geographic DTN Routing with Navigator Prediction for Urban Vehicular Environments	GeoDTN+Nav	[27]
		A Novel Cross-Layer Optimized Position-Based Routing Protocol for VANETs	CLWPR	[28]
		Reliable Position-Based Routing Algorithm in Vehicular Ad Hoc Network	RPBR	[29]
		Position-Based Routing Algorithm for Improving Reliability of Inter-Vehicle Communication	RIPR	[30]
		A Link Quality Prediction Metric for Location Based Routing Protocols in Vehicular Ad Hoc Networks	LQPM	[31]
		Location Prediction for Grid-Based Geographical Routing in Vehicular Ad Hoc Networks	GPGR	[32]
	Geocast/Broadcast Multicast-based Routing	Trajectory-Based Coverage for Geocast in Vehicular Networks	CAG	[33]
		DG-Castor for Query Packets Dissemination in VANET	DG-CastoR	[34]
		Exploiting Trajectories for Multicast in Sparse Vehicular Networks	TMC	[35]
		A Novel Multi-Cast Routing Protocol for VANET	MRP	[36]
		Position Prediction Based Multicast Routing (PPMR) Using Kalman Filter over VANET	PPMR	[37]
		Reliable Broadcast Routing Scheme Mobility Prediction for VANET	RB-MP	[38]
Data Forwarding		Shared-Trajectory-Based Data Forwarding Scheme	STDFS	[39]
		Travel Prediction Based Data Forwarding for Light-Traffic Vehicular Networks	TBD	[40]
		Trend-Prediction Based Geographic Message Forwarding in Sparse Vehicular Networks	Seer	[41]
		Design of Data Forwarding Strategies in Vehicular Ad Hoc Networks	DDFS	[42]
		Trajectory Improves Data Delivery in Urban Vehicular Networks	Trajectory-Dis	[43]
		Trajectory-Based Data Forwarding with Future Neighbor Prediction in Autonomous Driving Vehicular Environments	TFNP	[44]
		Delay Tolerant and Predictive Data Dissemination Protocol for Urban and Highway VANETs	DTP-DDP	[45]
		An Efficient Prediction Based Data Forwarding Strategy in Vehicular Ad Hoc Network	EPBDF	[46]
Traffic Management		Travel Time Prediction on Urban Networks Based on Combining Rough Set with Support Vector Machine	TTPOUN	[47]
		Travel-Time Prediction Using Gaussian Process Regression: A Trajectory-Based Approach	TTPUGPR	[48]
		Vehicle Travel Time Predication Based on Multiple Kernel Regression	MKLR	[49]
		Improved Travel Time Prediction Algorithms for Intelligent Transportation Systems	iSMA	[50]
		Travel Time Prediction Using Machine Learning	TTPML	[51]
		Genetic Algorithm Based Efficient RSU Distribution to Estimate Travel Time for Vehicular Users	ORTT	[52]
		Dynamic Highway Congestion Detection and Prediction Based on Shock Waves	DHCDP	[53]
		A Predictive Road Traffic Management System Based on Vehicular Ad Hoc Network	PRTMS	[54]
		Average-Speed Forecast and Adjustment Via VANETs	ASFA	[55]
		Vehicular Movement Patterns: A Prediction Based Route Discovery Technique for VANETs	PBRD	[56]
		Traffic-Known Urban Vehicular Route Prediction Based on Partial Mobility Patterns	TKUVRP	[57]
Road Safety		An Advanced Cooperative Path Prediction Algorithm for Safety Applications in Vehicular Networks	ACPP	[58]
		Cooperative Collision Warning Through Mobility and Probability Prediction	CCWS	[59]
		Disseminate Warning Message in VANETs Based on Predicting the Interval of Vehicles	DWMBPIV	[60]
		Development of Crash Prediction Models with Individual Vehicular Data	UFC	[61]
		Collision Risk Prediction and Warning at Road Intersections Using an Object Oriented Bayesian Network	CRPW	[62]
		Vehicle Motion Prediction and Collision Risk Assessment with a Simulated Vehicular Cyber Physical System	VMPCRA	[63]
		Intelligent Data Fusion System for Predicting Vehicle Collision Warning Using Vision/GPS Sensing	PVCWVGPS	[64]
General-Purpose		Movement Prediction in Vehicular Networks	MPVN	[65]
		A GPS-Free Method for Vehicle Future Movement Directions Prediction Using SOM for VANET	FMDP	[66]

	Practical Link Duration Prediction Model in Vehicular Ad Hoc Networks	LDP	[67]
	An Efficient Neighborhood Prediction Protocol to Estimate Link Availability in VANETs	NPP	[68]
	Potential Predictability of Vehicular Staying Time for Large-Scale Urban Environment	PPVST	[69]

4.5. General-Purpose

Unlike the above-mentioned protocols, a few subset of the predictive protocols can be classified as general purpose, in which they were designed without any specific application in mind [65-69]. A prediction method is proposed in [65] to determine the vehicle future steps by the probabilistic analysis of the vehicle current movement, while a GPS free method that uses the movement patterns of the vehicles is introduced in [66] to achieve the same objective. LDP [67], and NPP [68] aim to predict the availability and the duration of future links between vehicles through a mobility prediction model. Finally, the main objective of PPVST [69] is to predict vehicular staying time in different areas in large cities.

On the other side, we preferred to reference the proposed protocols in [70-71], even though we have not found many papers related to these protocols that entitle them to be categorized. However, mentioning them here might open the way for further studies that could take the advantage of the predictability of vehicles movement to improve another aspects of VANETs. PTMAC [70] is proposed to overcome the problem of packet collisions that might occur in the Time-Division Multiple-Access (TDMA)-based protocols. PTMAC proposed a novel way to predict encounter collisions for both two-way traffic and four-way intersections. V-PADA [71] addresses the problem of data access in VANETs. In V-PADA, a vehicle replicate its own data with the other vehicles in its platoon, in order to give them the ability to access its data even after it leaves the platoon. Therefore, a vehicle-platooning protocol is designed to identify platoon formation and predict platoon splits.

5. Taxonomy of Prediction-based Protocols in VANETs Based on their Prediction Objectives

In this section, the prediction-based protocols are reviewed and classified with reference to their prediction objectives, which is pivotal to understand the protocol behavior and function as opposed to purpose. As shown in Fig.5, the predictive protocols are classified in this article in terms of their prediction objectives into five main categories: 1) Link Stability Prediction, 2) Location Prediction, 3) Trajectory Prediction, 4) Travelling Time Prediction, and 5) Collision Prediction. Table 2 summarizes the proposed prediction-based protocols discussed in this survey, grouped by their main prediction objectives in addition to demonstrate the application, scenario, and simulator for each protocol.

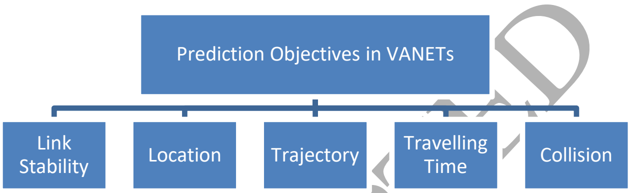


Figure 5 Prediction objectives of the prediction-based protocols in VANETs.

5.1. Link Stability Prediction

In general, data packets routed between source and destination vehicles traverse along paths that are composed of several communication links. Therefore, identifying and selecting the stable paths is a challenging issue to maintain a reliable communication environment in VANETs. The stability of the path depends on the stability of the links that constitute it. Typically, the stability of a communication link is expressed in terms of its lifetime [16]. The link lifetime is defined as the time duration since a vehicle enters the communication range of another vehicle till the instance the vehicle exits that range. The link lifetime between two connected vehicles is affected by several factors such as the movement directions of the vehicles as well as their relative speed and position. This section aims to give readers a glimpse about the various protocols that are predicting the link stability in VANETs.

PBR [15] aims to refine the reactive routing protocols by reconstructing routes proactively before they break. The predication algorithm predicts a lifetime for each route, then a timer equal to the predicted route lifetime is started at the source vehicle. The lifetime of a route is given as the minimum of its consecutive links lifetimes, while the link lifetime between two vehicles is predicted based on their communication range, separation distance, predicted velocities, and a specific parameter which is used to reflect whether the two vehicles are moving towards each other or away from each other. Consequently, the source vehicle tries to proactively discover a new route (if possible), prior to the expiration of the existing route, in order to preempt route failure.

MOPR [26] is proposed to improve the position-based routing for VANETs. In MOPR, link stability is estimated between each neighboring vehicles to characterize the quality of the communication link between them. The link stability is estimated in terms of communication lifetime between the constituent vehicles of the path through predicting the future location of forwarding vehicles. The link stability information is used to select the most stable path; it is expressed by path stability among source and destination vehicles. As a result, the probability of link failure is decreased by choosing the most stable route; hence, the communication overhead required to reconstruct routes is reduced.

Likewise, LQPM [31] introduced a novel combined metric, for predicting link quality under shadowing and fading effects in VANETs, in order to improve the position-based routing; the future link quality as well as the past link quality are examined for each vehicle. The future locations and the success rate of packets are used to estimate the future and the past link quality of a vehicle respectively. Among the neighbors of a forwarding vehicle, the vehicle with the highest combined link quality is chosen to be the next hop. The Expected Transmission Count (ETX) is developed to express the past link quality, while, the Predicted forwarding Progress Distance (PPD) is developed to express the future link quality.

Table 2: List of the prediction-based protocols in this survey grouped by their main prediction objective.

Prediction Category	Acronym	Citation	Application	Scenario	GPS Required	Simulator
Link Stability Prediction	PBR	[15]	Reactive Routing	Highway	No	Custom made
	MAODV-P/PF	[16]	Reactive Routing	Urban	No	Custom made
	MOPR	[26]	Position-based routing	Highway	No	NS2
	RIPR	[30]	Position-based routing	Urban/Highway	No	NS2
	LQPM	[31]	Position-based routing	Urban	No	QualNet
	MRP	[36]	Multicast Routing	Urban	No	GloMoSim
	EPBDF	[46]	Data Forwarding	Urban/Highway	No	ONE
	LDP	[67]	General-Purpose	Urban/Highway	No	VISSIM
	NPP	[68]	General-Purpose	Urban	No	NS2
	RB-MP	[38]	Broadcast Routing	Urban/Highway	No	Custom made
Position Prediction	MSBR	[19]	Reactive Routing	Urban	No	OPNET
	LPRV	[20]	Position-based routing	Urban	No	NS2
	FPBR	[22]	Position-based routing	Highway	No	OPNET
	MORA	[23]	Position-based routing	Highway	No	GloMoSim
	GRPL	[24]	Position-based routing	Urban	No	Custom made
	PHRHLS	[25]	Position-based routing	Urban	No	NS2
	CLWPR	[28]	Position-based routing	Urban	Yes	Custom made
	RPBR	[29]	Position-based routing	Urban/Highway	No	QualNet
	GPGR	[32]	Position-based routing	Urban	No	NS2
	PPMR	[37]	Multicast Routing	Urban/Highway	Yes	NS2
	DDFS	[42]	Data Forwarding	Urban	No	VISSIM
	DG-CastoR	[34]	Geocast Routing	Urban	No	GloMoSim
	MPVN	[65]	General-Purpose	Urban/Highway	Yes	NS2
Trajectory Prediction	Profile-BR	[17]	Reactive Routing	Urban/Highway	Yes	GloMoSim
	PSR	[18]	Reactive Routing	Urban	Yes	NS2
	AGP	[21]	Position-based routing	Urban	No	NS2
	GeoDTN+Nav	[27]	Position-based routing	Urban	Yes	QualNet
	CAG	[34]	Geocast Routing	Urban	Yes	Custom made
	TMC	[35]	Multicast Routing	Urban	Yes	Custom made
	STDFS	[39]	Data Forwarding	Urban	Yes	n/a
	TBD	[40]	Data Forwarding	Urban	Yes	Custom made
	Seer	[41]	Data Forwarding	Urban/Highway	Yes	ONE
	Trajectory-Dis	[43]	Data Forwarding	Urban	Yes	NS2
	TFNP	[44]	Data Forwarding	Urban	Yes	Custom made
	DTP-DDP	[45]	Data Forwarding	Urban	Yes	n/a
	PBRD	[56]	Traffic Management	Urban	Yes	n/a
	TKUVRP	[57]	Traffic Management	Urban	Yes	n/a
	ACPP	[58]	Safety Applications	Urban	Yes	NS2
	FMDP	[66]	General-Purpose	Urban	No	n/a
Travelling Time Prediction	TTPOUN	[47]	Traffic Management	Urban	No	n/a
	TTPUGPR	[48]	Traffic Management	Urban/Highway	Yes	n/a
	MKLR	[49]	Traffic Management	Urban/Highway	No	n/a
	iSMA	[50]	Traffic Management	Urban	No	n/a
	TTPML	[51]	Traffic Management	n/a	n/a	n/a
	ORTT	[52]	Traffic Management	Urban	n/a	n/a
	DHCDP	[53]	Traffic Management	Highway	No	n/a
	PPVST	[69]	General-Purpose	Urban	No	n/a
Collision Prediction	CCWS	[59]	Road Safety	Urban	No	n/a
	DWMBPIV	[60]	Road Safety	Highway	No	n/a
	UFC	[61]	Road Safety	Urban	Yes	n/a
	CRPW	[62]	Road Safety	Urban	No	n/a
	VMPCRA	[63]	Road Safety	Urban	No	n/a
	PVCWVGPS	[64]	Road Safety	Urban/Highway	Yes	n/a
Other	PRTMS	[54]	Traffic Management	Urban	No	n/a
	ASFA	[55]	Traffic Management	Urban/Highway	No	n/a

LDP [67], which does not assume that the vehicles follow certain mobility model, is proposed to allow vehicle to accurately estimate how long it will be connected to another vehicle. The major instrument of LDP is to approximate the distribution of relative speeds between vehicles besides considering the impact of traffic lights, the turning direction of the vehicles (at intersections), and their initial distances. The Exponential Moving Average (EMA) method is used to filter outliers by processing relative velocity samples. The simulation results show that only the latest ten relative speed samples are required by a vehicle to get an accurate estimation of the link durations between itself and any connected vehicles.

NPP [68] uses a mobility prediction model to anticipate the availability of future links between vehicles, in order to efficiently and effectively predict neighborhood occurrence. Subsequently, NPP is able to detect the topology changes earlier and provide a proper handling before it depreciates network performance. The neighborhood prediction is defined as the capacity of a vehicle to estimate when another vehicle will be in its communication range. The movement vectors of the vehicles are used by the NPP prediction model to estimate their future positions. Hence, NPP benefits of the information attached to periodic messages (beacons) that are broadcast further than one-hop neighbors.

MAODV-P/PF [16], which aims to improve reactive routing, is proposed as the core module to estimates the speed of a vehicle within the following time period. The mobility pattern of a vehicle is used as the input to the proposed fuzzy module; several parameters are used to define the pattern of a vehicle such as the distance between two consecutive vehicles, driver's age and the current speed. As the mobility may cause link breaks, the fuzzy module generates link break and congestion indicators to prevent those breaks. The results show that the proposed mechanism enhances the performance metrics and effectively prevent link breaks and congestion occurrence.

RB-MP [38] is a broadcast routing scheme proposed for VANETs to select the most stable route using the calculated relative speeds and the inter-vehicle distance of the neighboring vehicles. A Prediction Holding Time (*PHT*) is defined to ensure the reliability in the selection of the next rebroadcast vehicles. The PHT_{ij} characterizes the predicted time that vehicle *i* can stay in the communication range of vehicle *j*. the current positions, communication range and relative speed of both nodes are used to calculate their *PHT*.

RIPR [30] is proposed to improve the reliability of position-based routing through reducing the possibility of getting local maximum and link breakage problems. RIPR predicts the positions of relay candidates and selects the relay node based on the number of neighbors of the node as well as the road characteristics. For this purpose, a mobility prediction model is introduced to predict the moving velocities and moving directions of vehicles, which allows the sender to select the vehicle that has the largest relative velocity as the relay vehicle.

EPBDF [46] utilizes a new metric named link utility in the process of forwarder selection. Link utility reflects the impact of relative velocity and distance between the vehicles on the efficiency of inter-vehicle data transmissions. The proposed algorithm is used to minimize number of hops and optimize packet routing especially in the high-density VANETs.

Overall, the accurate prediction of the lifetime of the communication links results in decreasing the end-to-end delay and increasing the packet delivery ratio. Additionally, taking into consideration the availability of future links that might be established with a currently non-neighbor vehicle is beneficial to ensure a reliable communication in VANETs. However, the effective prediction of the link lifetime requires a complete view of the mobility characteristics for each moving vehicle, which results in an incurred communication and computational overhead to cope with the highly dynamic topology.

Even though the importance of assessing the adequacy of the used prediction models, most of the protocols did not show a precise evaluation to their prediction accuracy, an identification of the mobility models that are applicable to their protocols, or whether the proposed protocols are suitable for general or specific mobility models. Furthermore, there is no notable work about the ability of the proposed protocols to handle the sudden changes in the mobility characteristics of the moving vehicle.

5.2. Position Prediction

Predicting the vehicles future short-term positions is of vital importance to estimate the link lifetime between connected vehicles. Additionally, it has a considerable influence to improve the position/geographic routing as well as data forwarding protocols in VANETs. Therefore, several protocols that exploit the predictive physical location of the participating vehicles were proposed to improve the vehicular communication. The purpose of this section is to review the noted protocols for this objective.

MSBR [19] uses the mobility information included in beacons to select reliable intermediate vehicles in order to improve reactive routing. As well, LPRV [20] selects the intermediate vehicles with predicted future localization closer to the delivery destination in order to improve position-based routing.

MORA [23] improves the performance of position-based routing for VANETs through applying the prediction algorithm to Greedy Perimeter Stateless Routing (GPSR) [72]. MORA considers the directions of movement for neighboring vehicles and their physical location while choosing the next forwarding vehicle for a packet. MORA uses a novel routing metric, which is a linear combination of the novel target functional and the number of hops. Herein, the algorithm is completely distributed; each vehicle can calculate this linear combination independently. Basically, the algorithm considers the straight line between source and destination vehicles, then develops the target function which depends on the distance between the forwarding vehicle and that line in addition to the vehicle movement direction. The data messages are then routed using the calculated linear combination metric.

GRPL [24] is proposed to improve the position-based routing by exploiting the predictive location of vehicles. Thence, a prediction technique that is based on the current speed and heading direction of a vehicle is developed. Simulation results clearly show that GRPL is applicable and reduce the cost of location updates. In like manner and for the same purpose, PHRHLS [25] extends the hierarchical location service with a mobility prediction algorithm, which is coupled with the GPSR to enhance the routing performance with minimal localization overhead.

In a similar approach, CLWPR [28] is proposed to improve the efficiency of position-based routing protocol in an urban vehicular environment. The proposed protocol uses the navigation information and the prediction of the vehicle position to select the next hop among the neighbors of the forwarding vehicle. A novel forwarding metric is developed which depends on several parameters such distance, angle, utilization, SNIR and MAC frame error rate to improve the efficiency of the proposed protocol. Additionally, carry-n-forward mechanism is used as a recovery strategy in sparse networks to cope with the local maximum problem. The simulation results show that CLWPR increases packet delivery ratio.

In the same context, GPGR [32] aims to improve the position-based routing and overcome the local maximum problem and link loss in vehicular environment. The proposed protocol assumes that each vehicle has a digital map and it utilizes the GPS information to know its location. GPGR partitions the geographic area into distinct dimensional logical grids. Given any physical location, each vehicle can determine which grid it belongs to. GPGR predicts the exact moving position of a vehicle along the road grids using its movement information such as velocity, position, direction, and road topology.

On the other side, PPMR [37] and MPVN [65] use a probabilistic analysis of the temporal and historical data of vehicle movements to determine its future positions. Navigation system, digital map, and GPS are used to collect the positions information of vehicles. Kalman Filter (KF) is used to remove the inaccuracies and fusion of the collected data, then the values from KF is used to find distances between vehicles.

On the whole, several parameters are used to predict vehicle future positions, such as historical data of vehicle movements, heading direction of a vehicle, current speed, navigation, and GPS information. However, the accurate prediction of the future vehicles positions requires precise characterization of several mobility constrains that are not addressed till now, such as density of vehicles, drivers' intentions, street map structure, and inter-vehicle behavior in urban or topographical circumstances.

Moreover, most of the proposed protocols are dependent on the availability of the GPS information when predicting the future positions of the vehicles, which weakens their robustness and violates the self-dependent nature of VANETs. Therefore, developing a light-weight GPS-free positioning system is necessary to provide efficient and reliable position-based predictive protocols.

The performance results of the predictive position-based protocols show a noticeable increase in the data delivery ratio. However, a remarkable increase in the control overhead and the end-to-end delay are shown as well. Therefore, position prediction is not recommended for Quality of Service (QoS) constraint applications. Moreover, coping with the problem of local maximum is still challenging.

5.3. Trajectory Prediction

The availability of a complete view of the vehicles future paths is valuable to create efficient multicast/geocast transmissions as well as data dissemination and forwarding protocols in sparse vehicular networks. Hence, predicting the future trajectories of vehicles could describe its ability to deliver a message to the desired destination. A vehicle can be considered capable of delivering a message to a desired destination either directly (its future trajectory overlaps the destination), or indirectly (the vehicles to be encountered overlaps that destination). This section provides a brief review of the literature on the trajectory prediction in VANETs.

GeoDTN+Nav [20] is presented as hybrid geographic routing solution to enhance the standard GPSR by exploiting both of the vehicular on-board navigation system and the vehicular mobility. The Virtual Navigation Interface (VNI) is proposed to extend generalized route information and help in discovering the potential vehicles that can deliver packets in partitioned networks. The results show that GeoDTN+Nav increases the packet delivery ratio compared to other geographic routing protocols.

In order to improve the geocast routing in vehicular networks, the coverage capability is developed [26] to characterize the ability of a vehicle to deliver a message to the target region of the message within a time constraint. The data set of real vehicular GPS traces is used to verify that the travel time of a vehicle follows the Gamma distribution and maintain accurate prediction of the arrival time of a vehicle at a given location on its trajectory. The extensive trace driven simulations show that the proposed distributed algorithm that takes the advantage of the coverage capability as a message forwarding metric increases the message delivery ratio with low communication overhead.

TMC [28] exploits the trajectories of vehicle to create efficient multicast transmissions in sparse vehicular networks. TMC chooses the forwarder vehicle that has the highest capability to deliver the message to more destinations. Hence, a forwarder vehicle of a message is chosen if it has the ability to encounter more destination vehicles. However, the lack of accurate timing information makes the predication of encounter between two vehicles a challenging issue. There are two necessary conditions to encounter vehicles. Firstly, the two vehicles must have a common trajectory intersection. Secondly, the arrival moments of both vehicles at that intersection are relatively close in order to be within the communication range of each other. Hence, the probability of encounter between two vehicles is computed based on the aforementioned conditions given their trajectories.

STDFS [31] exploits the cooperation between vehicles in sharing the trajectory information to get over the statistics uncertainty and achieve accurate data forwarding. STDSF constructs a predicted encounter graph using the predicted encountering events between vehicles. Due to the dynamic expansion of the predicted encounter graph, STDSF ameliorates the forwarding sequence in respect of delivery delay and delivery ratio, in addition to determine the appropriate forwarding metrics, which allows vehicles to select the best forwarder among its neighbors. Similarly, TBD [32] constructs a vehicle encounter graph for light-traffic vehicular networks to predict vehicle encounter events, which is used to optimize data forwarding process for minimal data delivery delay under a specific delivery ratio threshold

TFNP [36] is tailored to improve the data forwarding in autonomous driving vehicular environments, in which the future neighbors of each vehicle is identified using the trajectory information of all autonomous vehicles. Firstly, the proposed scheme analyzes the trajectory information of all autonomous vehicles to predict the future neighbors of each vehicle; and secondly that prediction of the future neighbors of vehicle is used to generate the forwarding sequences, which is used when an autonomous vehicle needs to transmit messages. The simulation results show that TFNP scheme improves the data delivery ratio with an average end-to-end delay.

DTP-DDP [38] which takes the advantage of the GPS with integrated maps is proposed to enhance data dissemination within a certain area of interest for urban and highway VANETs. The data sender elects the further vehicles that will rebroadcast the information by utilizing the data from a map together with its predictive mechanism. The simulation results show that the proposed scheme alleviates the broadcast storm problem while keeping delivery ratio on a par with the flooding scheme by sacrificing some delay performance. Likewise, AGP [14] uses the kinematics parameters and the map information to predict the vehicle trajectory in city environment. The predictive mobility improve the routing discovery procedure in which the destination moves away from its location. The simulation results show that AGP improve packet delivery ratio with an average number of hops. An advanced cooperative path prediction algorithm is proposed in [58] to predict the future path of the vehicles. The proposed algorithm uses velocity, acceleration, position, heading, and map data for the road geometry.

On the other hand, due to the repetitive nature of the most trips that are made by the vehicles; thus, extracting the movement pattern of the vehicle from its movement history are used in order to predict its next direction. Several algorithms are proposed [17, 18, 43, 56, 57 and 66] to predict the future trajectory of the vehicle by extracting its movement pattern.

A new method to reduce the links breakages between communicating vehicles is introduced based on the vehicle trips history [17] in order to enhance reactive routing. The basic idea of the proposed method is to extract the movement pattern of each vehicle from its trip history to derive its own profile. This profile is used to predict the next direction of the vehicle at the next junction and is sent to its neighbors. The routing protocol is modified to use the predicted directions in the next hop selection process as each vehicle tries to select a vehicle in which its future direction is the same as its predicted direction. The proposed algorithm is composed of three components: 1) Trip Extraction (TE), 2) Pattern Extraction (PE), and 3) Future Direction Prediction (FDP). The proposed TE assumes that each vehicle is equipped with a GPS receiver to determine its location and it extracts discrete trips for each vehicle from its GPS raw data. The movement patterns of a vehicle are extracted by applying PE on their extracted trips. The future trip of the vehicle would be predicted according to this retrieved pattern. The simulation results show a notable decreasing in the number of link breakages, especially with high speed and low transmission range.

PSR [18] aims to improve the performance of reactive routing by identifying the mobility pattern of the moving vehicles. PSR takes the advantage of Vehicle Mobility Pattern (VMP), which is abstracted from the real trace data in Shanghai by using Variable-order Markov Model (VMM), in which the disseminated state information carries the current state and the predictive states of a vehicle. PSR is composed of three components: 1) Location Information Propagation, 2) Data Packet Forwarding, and 3) Prediction Error Recovery. The performance evaluation via simulation shows that PSR improves packet delivery ratio, packet delivery delay, and control packet overhead. Similarly, Trajectory-

Global and Trajectory-Distributed algorithms which based on extracting the movement pattern of a vehicle are proposed [43] to enhance data forwarding, the proposed algorithms aim to predict accurately the future trajectories of a vehicle using multiple order Markov chains.

In order to enhance traffic management, an analogous work is presented in [57] where VMMs are applied on the real taxi GPS trace data collected in Shanghai to obtain mobility patterns. The trace-driven simulation results show that using multiple VMMs, notable patterns can be mined from routes of common vehicles, and hence high route prediction accuracy can be achieved.

A novel GPS-free method is proposed in [66] to predict the vehicle next movement direction at each junction. The proposed method uses a competitive neural network, which is called Self Organizing Map (SOM) to cluster the vehicle motion paths in order to extract the movement pattern of the vehicles. The extracted patterns are then used to predict the next direction, which will be chosen by the vehicle at the next junction. The results show that the accuracy of the proposed method is approximately in equal standing with the other GPS-dependent methods; however, the proposed method has a notable advantage when GPS- dependent methods encounter GPS obstacles (high-rise buildings, high trees, tunnels, etc.).

By and large, the navigation systems are used to propose a path to the desired destination. Thus, several protocols utilize the navigation information with integrated maps in order to predict the future trajectories of vehicles. Similarly to the position prediction drawbacks, the necessity of the GPS information makes the trajectory prediction more prosaic, due to the onerousness of maintaining precise GPS information and the suffering from positioning errors and fluctuations from the actual path. Moreover, this approach requires more time to predict the future vehicle trajectory and leads to incurred computational overhead.

Above all, sharing the trajectories of the vehicles in a privacy-preserving manner is always challenging. Furthermore, predicting the accurate arriving time of a vehicle at each location along its predicted future trajectory is pivotal to achieve the full advantages from the predicted information.

5.4. Travelling Time Prediction

Predicting the vehicular travelling time is considered a motivating topic in the present transportation research. Different from the position and trajectory prediction that mainly depend on the movement regularity of individual vehicle, the traffic status has a primary influence on predicting accurately the vehicles travelling time, which plays a key role in enhancing traffic management applications and designing efficient dynamic transportation systems. The requirements of these applications are not only limited to the accuracy of prediction, but also expanded to include fast and on-line prediction.

Until now, several methods are used to predict the travelling time, such as linear regressing model, mathematical statistics, neural network, historical trend extrapolation, Kalman filter and time series method.

A recent method, that combines Support Vector Machine (SVM) and rough set, is proposed in [47] to ameliorate the exactness of predicting the travel time on urban networks. SVM has derived from the machine learning community [73]. Additionally, the network scale can be reduced by excluding the redundant traffic data.

The released travel time prediction consists of two main components, rough set data pre-processor and SVM regression. Foremost, the rough set is used to pre-process the unrefined traffic data, which is comprised of the occupancy ratio, travel time, and traffic volume. Consequently, the SVM is trained to predict the travel time using the outcomes as input samples. Four successive steps are included in that model, constructing the decision table, choosing the SVM input samples, SVM training, and predicting the travel time.

A method is proposed [48] to predict the travel time of a casual path that includes links with little data about the traffic history. The kernel function is produced to define the similarity between paths, while predicting the travel time is achieved probabilistically by applying the Gaussian process regression.

The Multiple Kernel Learning Regression (MKLR) [49] technique is used to predict vehicle travel time. The proposed model consists of three steps: 1) Preprocessing historical data, in order to immediately normalize different dimensions data, 2) Training the historical data and performing analysis, and 3) Predicting the vehicle travel time based on the trained model.

Improved Successive Moving Average (iSMA) and Improved Chain Average (iCA) Algorithms are proposed [50] to improve the travel time prediction for VANETs. Non-recursive equations are used by both algorithms to compute the predicted travel time. Both time and space required for prediction are reduced while maintain the prediction accuracy. Experimental results showed that the proposed algorithms improved travel time prediction.

The travel time of a vehicle between any two points in an approximated area is predicted using the machine learning technique [51]. The historical data of a vehicle movements combined with a set of semantic variables are used in a learning process to predict the travel time accurately. Although this is preliminary work, the results were satisfactory.

ORTT [52] is proposed to calculate the travel time of a vehicle using a genetic algorithm. ORTT utilizes the RSU to achieve the required objective. The proposed algorithm aims to optimize the number and the right locations of RSUs in order to maintain accurate travel time prediction with minimum VANET infrastructure cost.

A novel aspect of predicting the travelling time of a vehicle is to predict its own staying time in different regions, which is needed to estimate the vehicular traffic and further predict the congestion events [69]. Predicting the staying time for a vehicle at a specific area depends on the historical staying times of the other vehicles as well as the vehicle itself.

For the most part, the current researches commonly focus on predicting the travelling time in single road conditions and a relatively narrow range lane by utilizing traffic data for short term traffic prediction. In addition, all the methods require performing a huge amount of data analysis, which increases the computational overhead in order to conduct accurate prediction.

5.5. Collision Prediction

Avoiding the traffic accidents is a popular research topic in the field of the ITS. Here, driver's distraction can be considered as the main cause of traffic accidents, and the rate of the accidents can be reduced if the drivers can detect the accident risk at a proper time to take the appropriate action. Therefore, predicting the collision risk is introduced as an efficacious solution to improve road safety applications.

CCWS [59] derived an analytical expression of mobility parameters (speed, acceleration, and relative distance), and followed a statistical approach to characterize the conditional probability of a collision in order to predict it. Two collision prediction algorithms using these expressions are proposed. The weighted collision prediction which combines all of the presented parameters to predict the collision to improve the accuracy of prediction, and priority based prediction which checks those parameters sequentially according to a given priority to ease the implementation. The preliminary numerical results have demonstrated the effectiveness of the proposed analytical derivations.

UFC [61], which depends on several parameters (speed of leading and following vehicles, deceleration rate, gravity acceleration, time headway, and perception reaction time of the following vehicle), is proposed as a novel measure of safety that is based on individual vehicular data, and then used to predict the crash potential between two consecutive vehicles. Statistical crash prediction models including hurdle models are developed using individual vehicular data and crash data. The results of applying the UFC to basic sections of interstate highways in Virginia showed a promising potential of the aggregated UFC measure to effectively predict traffic crash occurrence. However, several improvements could be done to validate the efficacy of the UFC such as collecting additional individual vehicular data on more roadway segments and for a longer time period.

A collision avoidance system, which utilizes driver behavior, predicted vehicle motion/location, and road geometry information, is developed in [63]. Initially, the proposed system uses the Kalman Filter (KF) algorithm and the vehicle motion model to predict the short-term motion of the objective vehicle and surrounding vehicles. Then, the driver behavior and road curvature are considered to predict vehicle location and compute the traveled distance among vehicles in real-time. Finally, the vehicle collision risk is predicted by comparing the predicted vehicle gaps with a safe distance threshold. The simulation results demonstrate that the proposed system is effective for predicting collision risk and providing accurate warnings in a timely fashion.

On the other hand, Object Oriented Bayesian Network (OOBN) is used in [62] to analyze collision situations at road intersections. The OOBN is designed in two levels in order to predict a possible collision and assess the collision probability. The first OOBN-level checks the conditions for simultaneous occupancy of the conflict area to determine the probability of potential collisions. The second OOBN-level incorporates the likelihood of the particular conflict area to decide the probability of real collision. The experimental results show that the proposed system can predict the collision to two seconds before a possible impact in different situations without producing any false negative and false positive warnings.

In short, predicting the collision risk depends on several correlated factors such as those associated to vehicle, driver behavior, traffic status, road geometry, and environmental conditions. A wide range of statistical crash prediction models are developed using individual vehicular data and crash data for modelling traffic collisions, such as Poisson regression, Negative Binomial regression, Zero-Inflated models, logit and probit models, and machine learning methods [74-76].

However, it is very difficult for these models to accurately estimate the collision occurrence, because of the complexity of deriving the required parameters, which impedes the adequate prediction of collision.

6. Analysis and Comparisons

In order to complete the study of the prediction-based protocols in VANETs, it is essential to determine the suitability of the prediction objectives to the various applications, identify the performance metrics for each prediction objectives, and discuss the prediction-related research challenges.

6.1. Usage Analysis

The usage percentage of the prediction-based protocols in VANETs with respect to their prediction objectives, applications, and scenarios are shown in Fig.6. Furthermore, Fig.7 and Fig.8 show the distribution of the applications and scenarios with respect to the prediction objectives, which could help to recognize the appropriate use of each prediction objective to the various applications. The analysis of the results can be summarized as follows.

Predicting the link stability is not dedicated for a specific type of application, this could be explained by the fact that maintaining a stable communication between connected vehicles is a common requirement of the various applications. Although predicting link stability is used in both urban and highway scenarios, it is more crucial in the highway scenario as the link lifetime between communicating vehicles in highways is higher and more predictable than in urban scenario.

On the other hand, predicting the future trajectories of the vehicles is mostly used to improve data forwarding protocols, because the early knowledge of the future trajectories allows selecting the vehicle that could provide the best forwarding performance. Differently, predicting the short-term future positions of the vehicles is commonly used to improve position-based routing protocols, as they are highly dependable on the physical location of the candidate relay vehicle.

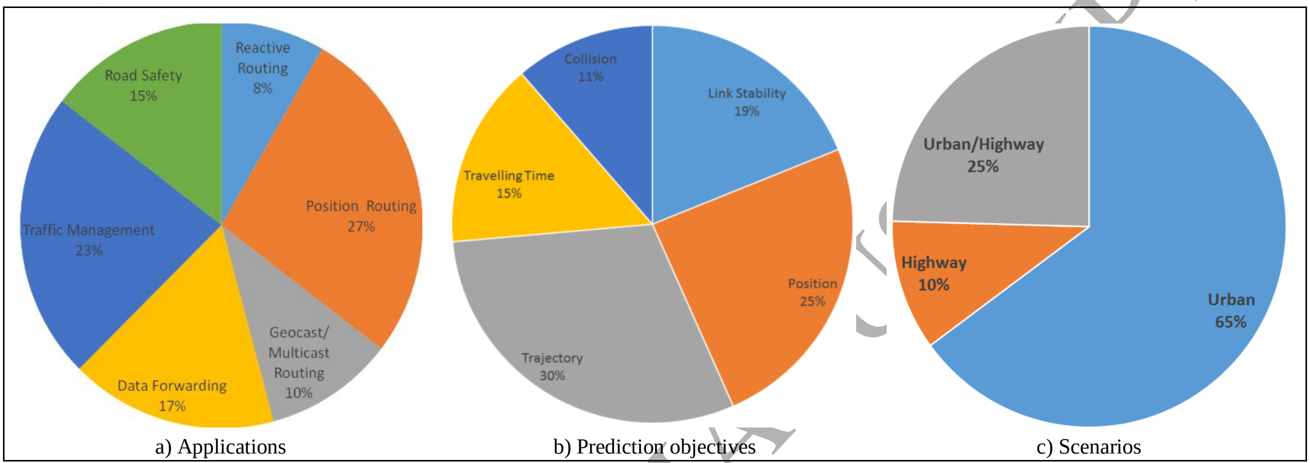
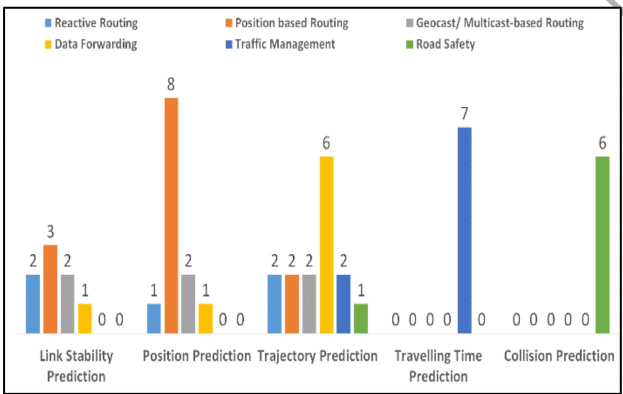


Figure 6 Usage analysis of the reviewed articles with reference to a) Applications, b) Prediction objectives, and c) Scenarios



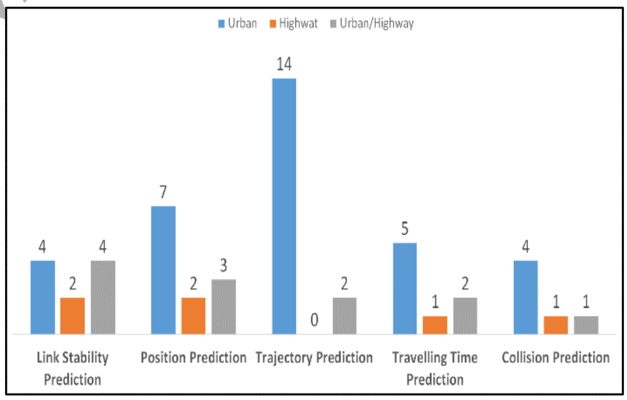


Figure 7 Distribution of scenarios with respect to the prediction objectives

Figure 8 Distribution of applications with respect to the prediction objectives

Hence, predicting the future location of the neighbors' vehicles may give the forwarding vehicle good visibility to select the optimal relay vehicle. Both trajectory and position prediction are used mostly in urban scenario, this could be explained because the urban layout has several intersections and junctions, which give the vehicles more directions that might be predicted instead of the highways which have limited movements' directions.

On the other side, the traffic management applications are improved through predicting the vehicle travelling time, which helps the ITS to estimate traffic congestion and enhance the accuracy of the transportation systems. The road safety applications are improved by predicting the collision risk in order to provide accurate warning in a timely fashion. As the possibility of car accidents increases at the intersections, the predictive protocols that aim to predict the collision risk focus on the urban scenario.

6.2. Performance Comparisons

In VANETs, performing an experimental evaluation of a novel protocol is a complex and expensive task. Thus, most authors proposing novel predictive protocols evaluate the performance of their new protocols using simulations, in which several performance metrics are compared against one or more alternative protocols that have been proposed for the same purpose. Commonly, prediction-based routing and data forwarding protocols use the packet delivery ratio, end-to-end delay, broken link ratio, and control overhead in order to demonstrate the efficiency of the proposed protocols, while traffic management and road safety predictive protocols use the prediction accuracy as the primary metric to evaluate their performance.

Because of the importance of evaluating the performance of the predictive models, a performance comparison is given to complement this study. The performance results are extracted from the original work of the proposed protocols. Verification and validation of the given results is out of this article scope. The results of the performance metrics are categorized into three categories; high, medium, and low according to the percentage of improvement in the performance metric with reference to the compared protocols. As we have noticed, the percentages of improvement are ranging from 0% to 45% and have almost normal distribution. Consequently, the equal interval classification method is used to divide the range of the percentage of improvement into three equally sized categories as shown in Table 3.

Table 3: Categories of the performance metrics results

Category	Percentage of the improvement in performance metric with reference to the compared protocols
High	31 % – 45 %
Medium	15 % – 30 %
Low	0 % – 14 %

Table 4 shows the performance evaluation of the predictive routing and data forwarding protocols in terms of their commonly used metrics, the protocols are sorted from newest to oldest in order of the date of publication. Table 5 shows the average evaluation of each prediction objective category with respect to the various applications of the prediction-based protocols.

The performance comparisons show that predicting link stability has a significant effect on increasing packet delivery ratio with low overhead and time delay when being utilized with the reactive routing protocols, while it shows only a slight improvement when it is used with the position-based routing and data forwarding. The position prediction improves packet delivery ratio when being utilized with position-based routing and data forwarding protocols, but it shows high control overhead and average end-to-end delay as well. Similarly, the trajectory prediction increases the packet delivery ratio when it is used to improve routing and data forwarding protocols with average control overhead and high end-to-end delay.

Table 6 shows the performance evaluation of the safety predictive protocols, which mainly measure the efficiency of detecting collision risk and providing accurate warnings in a timely fashion, the protocols are sorted from newest to oldest in order of the date of publication.

On the other hand, Table 7 shows the performance evaluation of the predictive traffic management and general purpose protocols in terms of their prediction accuracy, the protocols are sorted from newest to oldest in order of the date of publication. However, the predictability limit of those protocols has mainly been analyzed by informal means only. Therefore, a mathematical framework in which the predictability can be precisely defined is needed to evaluate the reviewed articles.

6.3. Prediction-related Research Challenges in VANETs

Despite the potential benefits, the predictive protocols that have been proposed are hampered by a number of fundamental and critical challenges, which need to be adequately addressed. This section summarizes the prediction-related research challenges as follows:

i. Lack of formal predictability analysis, which allows all the pitfalls of informal prediction arguments to occur. Therefore, the evaluation and verification of the predictive protocols require a formal framework to analyze the predictability limits of the proposed protocols.
ii. Sharing the future movements and directions of the vehicles may violate the privacy of the vehicles and their driver's intentions. Therefore, taking the advantage of the predicted information of the vehicles while preserving their privacy is still an open research area.
iii. Although the proposed protocols seek to present their high prediction accuracy, there is no notable work that discusses the protocol behavior to recover from the false prediction.
iv. In spite of utilizing several characteristics of the vehicle mobility such as its current position, speed, acceleration, and movement direction in order to predict the required information, there are additional parameters that could be targeted to increase the potential of high prediction accuracy such as driver behavior, gender, age, traffic density, and weather conditions.
v. The high dependency of the predictive protocols on the shared information requires precise discussion about the ability to be resilient against several attacks that may target the proposed protocols.

vi. Several predictive protocols show their dependency on the availability of the GPS information. However, the ad hoc nature of VANETs motivates the desire to develop a predictive protocol that does not rely on the GPS information.
vii. Dissimilarity in simulations scenarios and nomenclature of performance metric between publications, even for protocols designed for the same application, necessitates standardization of the validation methodology. Moreover, encouraging the free availability of the source codes would allow fellow researchers to quickly benchmark their proposals with reference to the previously published protocols.
viii. There are various other aspects in VANETs that need further studies to show their ability to get benefited from the predictable information such as clustering, localization techniques, and channel access management.

7. Conclusion

Due to the highly dynamic topology of VANETs, modeling and predicting the vehicle mobility could play a key role in designing efficient communication protocols. Fortunately, the movements of the vehicles are usually constrained along roads and streets. Therefore, the future movements of the vehicles are predictable. In the literature, numerous prediction-based protocols are proposed to enhance several aspects of VANETs.

In this paper, a literature review of prediction-based protocols for VANETs is presented with reference to their application, prediction objective, and performance metrics. Additionally, two novel taxonomies of these protocols are provided. The first one classifies the prediction-based protocols according to the main purpose of the proposed protocols, while the second taxonomy classifies them according to the prediction objective that the proposed protocols aim to predict. A discussion on each category is provided with a focus on the requirements, constrains, and

Table 4: performance evaluation of reactive, position-based, multicast, and geocast routing/data forwarding predictive protocols

Acronym	Packet delivery ratio	End-to-end Delay	Broken Link Ratio	Control Overhead	Comparisons
DTP-DDP	Medium	High	n/a	n/a	Epidemic
PPMR	n/a	n/a	Low	Low	PPUR
TBD	Medium	Medium	n/a	Low	VADD
TFNP	Medium	High	Medium	n/a	STDFS
LPRV	High	n/a	Low	Low	SIFT Flooding
RPBR	High	High	n/a	n/a	GPSR
MSBR	Medium	High	n/a	Low	n/a
MRP	High	Low	n/a	Medium	I-AODV
TMC	High	Medium	n/a	Low	Epidemic RAPID
EPBDF	Medium	Medium	n/a	Medium	TSF VADD
GRPL	Low	High	n/a	Low	GPSR
CAG	High	n/a	n/a	Medium	Epidemic, GPSR
LQPM	Medium	Medium	Medium	Medium	GPSR
Profile-BR	n/a	n/a	Low	Low	ROMSGP
Trajectrory-Dis	High	n/a	n/a	Low	Epidemic MobySpace
PHRHLS	Medium	Medium	n/a	Medium	GPSR
FPBR	Medium	Medium	n/a	n/a	DDOR
PSR	High	Medium	n/a	Medium	WSR
CLWPR	High	High	n/a	n/a	GPSR
AGP	High	High	Medium	n/a	AODV
RIPR	Medium	Medium	Low	n/a	GPSR GPCR
GPGR	High	n/a	n/a	n/a	GPSR GPCR
STDFS	High	Medium	n/a	Medium	TSF VADD
Seer	High	Low	n/a	n/a	Random
GeoDTN+ Nav	High	Medium	n/a	Medium	GPSR
DDFS	Medium	Medium	Medium	High	n/a
MAODV-P/PF	High	Low	n/a	Low	AODV
DG-CastoR	n/a	Medium	n/a	Low	n/a
MOPR	Medium	Medium	n/a	High	MORA GPSR
PBR	High	Low	n/a	Medium	Reactive Proactive
MORA	Medium	Medium	n/a	Medium	DSR AODV

Table 5: average evaluation of each prediction objective category with respect to the various applications

Prediction Category	Packet Delivery Ratio	End-to-end Delay	Broken Link Ratio	Control Overhead
Reactive Routing				
Link Stability Prediction	High	Low	Low	Low
Position Prediction	Medium	High	Low	Low
Trajectory Prediction	Medium	Medium	Low	Low
Position-based Routing				
Link Stability Prediction	Medium	Medium	Low	Medium
Position Prediction	High	Medium	n/a	Low
Trajectory Prediction	High	High	Medium	n/a
Multicast and Geocast Routing				
Link Stability Prediction	High	Low	n/a	Medium
Position Prediction	n/a	Medium	Low	Low
Trajectory Prediction	High	Medium	n/a	Low
Data Forwarding				
Link Stability Prediction	Medium	Medium	n/a	Medium
Position Prediction	High	High	Medium	Medium
Trajectory Prediction	High	Medium	Medium	Medium

Table 6: performance evaluation of safety predictive protocols

Acronym	Efficiency of detecting collision risk and providing accurate warnings in a timely fashion	Comparisons
VMPCRA	High	n/a
CRPW	High	n/a
UFC	High	n/a
CCWS	Low	n/a
DWMBPIV	Medium	n/a
PVCWVGPS	Medium	n/a

Table 7: performance evaluation of traffic management and general purpose predictive protocols

Acronym	Prediction Accuracy	Comparisons
MPVN	Medium position prediction accuracy	n/a
ORTT	Optimizes the number of RSUs for estimating the travel time	n/a
LDP	High link lifetime prediction accuracy	n/a
MKLR	High travelling time prediction accuracy	LSR
PRTMS	Improved total journey time and waiting time of the vehicles	n/a
PPVST	High staying time prediction accuracy	n/a
ASFA	Medium average speed Prediction accuracy	hybrid approach
PBRD	High route prediction accuracy	n/a
FMDP	High direction prediction accuracy	RPTO
iSMA	High travelling time prediction accuracy	iMKC
TTPOUN	Improved travel time predicting accuracy and velocity	single SVM
TTPML	Low travelling time prediction accuracy	n/a
DHCDP	High traffic congestion prediction accuracy	n/a
TTPUGPR	High travelling time prediction accuracy	n/a
TKUVRP	Medium route prediction accuracy	n/a
NPP	High neighborhood prediction accuracy	n/a

challenges. In order to complement this study, usage analysis and performance comparisons of the prediction-based protocols in VANETs are presented. The analysis derives the suitability of the prediction objectives to the various applications

In conclusion, predicting the link stability is vital to increase the performance of reactive routing protocols in VANETs, while predicting the future location or trajectory of the vehicles is useful to enhance the position-based routing and data forwarding protocols. Traffic management can be improved by predicting vehicle traveling time, and road safety could take the benefits of predicting the collision risk.

However, the unique characteristics of VANETs arise the need to an in-depth study for the feasibility of the prediction-based protocols to overcome the existing challenges and the open research areas. Additionally, there are many research issues to be addressed in mobility prediction such as clustering, quality of service, and prediction of mobility rules. Given that such predictive protocols involve the characteristics of mobile vehicles in their routing decisions, adopting the behavior of a driver in the prediction algorithms may be appropriate to safeguard more efficient and realistic predictions. The driver behavior has a significant influence on the patterns of mobility in both long and near terms. Thus, the development of new algorithms that can predict driver intentions may contribute to accurate predictions of an efficient route.

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