A Comprehensive Survey of the Key Technologies and Challenges Surrounding Vehicular Ad Hoc Networks

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Vehicular ad hoc networks (**VANETs**) and the services they support are an essential part of intelligent transportation. Through physical technologies, applications, protocols, and standards, they help to ensure traffic moves efficiently and vehicles operate safely. This article surveys the current state of play in VANETs development. The summarized and classified include the key technologies critical to the field, the resource-management and safety applications needed for smooth operations, the communications and data transmission protocols that support networking, and the theoretical and environmental constructs underpinning research and development, such as graph neural networks and the Internet of Things. Additionally, we identify and discuss several challenges facing VANETs, including poor safety, poor reliability, non-uniform standards, and low intelligence levels. Finally, we touch on hot technologies and techniques, such as reinforcement learning and 5G communications, to provide an outlook for the future of intelligent transportation systems.

CCS Concepts: • **Networks** → *Network architectures*; *Network protocols*; *Network security*;

Additional Key Words and Phrases: Vehicular ad hoc networks, VANETs, machine learning, deep learning, graph neural networks, reinforcement learning, emergency message broadcast

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1 INTRODUCTION

As the latest achievement in the **Internet of Things** (**IoT**), **vehicular ad hoc networks** (**VANETs**) are an essential part of modern intelligent transportation systems. They are tomorrow's control centers of urban traffic management, distributing information between vehicles, infrastructure, and authorities to ensure safe, efficient, and comfortable driving experiences for everyone on the road [4, 20, 23, 48, 49, 53, 55, 80, 96, 146]. Much research has been done to develop VANETs to where they are today. However, there is much, much more still to do. Hence, as a guide for new researchers in this emerging field, this survey provides a detailed overview of the past, present, and future of VANETs research and development. We summarize and categorize the theory and practice of research to date, identify several challenges currently facing VANETs, and discuss the technologies and techniques that will underpin the likely future of intelligent transportation systems. To begin the survey, this introduction provides a primer on VANETs, followed by a brief history of intelligent transport systems, and the key research topics that have occupied interest in the field.

The services VANETs provide range from traffic forecasting [40, 98] and resource scheduling [74, 120] to accurate positioning [167, 168] and emergency message broadcasting [2, 73], from intersection management [6, 19] to vehicle security and early warning systems for faults or breaches [111, 139]. Additionally, VANETs are the orchestrators that prevent collisions between autonomous vehicles [93]. All these services depend on communication and data exchange both between vehicles and between vehicles and other infrastructure. Hence, communication protocols, data formats, and standards to ensure compatibility between the diverse entities populating VANETs are important aspects of this field.

Beyond improving traffic safety and efficiency, VANETs have much to offer. For a start, improving traffic safety and efficiency both have significant economic impacts. Additionally, VANETS can help to reduce energy consumption—a point that has attracted a great deal of interest from governments, industry, and academia the world over. The US, the EU, and Japan are just some of the regions involved in developing VANETs and other advancements in intelligent transportation. For example, as far back as 1991, the U.S. Congress passed the **Intelligent Vehicle Highway Systems** (**IVHS**) plan, which called for the **Department of Transportation** (**US DoT**) to study how VANETs might be used to improve traffic safety, increase road efficiency, and reduce the environmental pollution associated with fossil fuels. By 1996, the US had established the "**Intelligent Transportation System** (**ITS**) Standards Program."

Over the next two decades, researchers and innovators would develop a host of disparate systems and technologies spanning everything from speed cameras to driverless cars, and, gradually, these innovations coalesced into larger, more collaborative IoT-style systems. In 2014, the US DoT's ITS joint program office released its strategic plan for the next 5 years (2015–2019). The aims were simple and forthright: improve vehicle and road safety, increase vehicle efficiency, and reduce the environmental impact of road transportation. The suggested priorities for achieving these goals included better collision avoidance algorithms, better management measures, and better communication mechanisms. In the next few years, the EU would also issue its strategy, calling for large-scale, co-operative intelligent transport across Europe by 2019. Again, improving communications was a prominent concern, with calls for advances in both **vehicle-to-vehicle** (**V2V**) and **vehicle-to-infrastructure** (**V2I**) communications. Japan's goals included stepping up its development of VANETs and automation technologies and a specific objective to build a world-leading intelligent transportation system before 2020. China joined the suit in 2017, when its **Ministry of Industry and Information Technology** (**MIIT**) issued guidelines to establish a national system of industrial standards to support assisted and autonomous driving. The guidelines call for standards over low-level autonomous driving to be in place by 2020, followed by standards for high-level autonomous driving in 2025. High-level driving functions include intelligent, automatic vehicle controls; network-based collaborative decision-making; and technical requirements related to scenario-specific driving.

With the world's richest nations all publicly professing capital investments into intelligent transport systems over the coming years—both financial and intellectual—it is unsurprising that VANETs have developed into a major research area in recent years. To date, most of the theoretical research on VANETs has focused on three key issues: methods of information collection and transmission; modes of intelligent decision-making by vehicles and roadside units; and solutions to the instability of communications.

As evidenced by the focus given to improving communications technologies in national strategies, network instability is one of the biggest challenges facing VANETs. Because vehicles move, the topological structures in VANETs are constantly changing. Hence, interruptions and failed connections would be the norm without innovations to ensure otherwise. Among the studies on this issue, Al-Sultan et al. [7] start from the ground up, outlining the features, functions, and communication modes of application units, roadside units, and on-board units. Cooper et al. [30] explore clustering techniques for VANETs, summarizing how they can be applied to solve the problems of routing protocol stability and scalability.

Notable studies on information collection and decision-making include Bila et al. [16], who summarize the various methods VANETs rely on to detect vehicles, roads, and pedestrians. Additionally, they outline methods of collision avoidance using information and communication technologies and conduct an in-depth analysis of VANETs' security mechanism based on visual and sensor data. Taking a different angle, Hasrouny et al. [42] focus on the characteristics, challenges, and requirements of VANET security, analyzing network attack models and corresponding solutions for the Internet of Vehicles. In meta-research, Eze et al. [35] review the research status of VANETs in terms of concepts, application, and research difficulties, while Karagiannis et al. [52] investigate the history of and civic interest in intelligent transportation systems starting with the Internet of Vehicles right through to projects pursued by the US, the EU, and Japan.

In short, the literature so far has only extended to a few aspects of VANETs. There is a great deal more that needs to be done on these and other topics, such as collaborative data acquisition for vehicles, data transmission, diverse network representations, AI integration and learning techniques, possible future directions of development, and so on. This is something we seek to rectify with this article. We hope that this guide for new researchers will inform and inspire keen interest in VANETs.

The rest of the article is organized as follows. Section 2 reviews applications in the two most common objectives of VANETs—efficiency and safety—and Section 3 summarizes the key technologies associated with data collection and transmission, routing protocols, and emergency message broadcasting. The current challenges facing the field are discussed in Section 4, and Section 5 outlines some potential future directions of research. The article concludes in Section 6 with a brief summary of the content covered.

2 COMMON APPLICATIONS

The ultimate goal of VANETs is to improve traffic efficiency and ensure safer travel. Largely, these objectives are accomplished through applications. Applications oriented toward efficiency mainly include traffic forecasting and resource scheduling, while safety-oriented applications include accurate positioning, intersection management, cooperative adaptive cruise control, vehicle safety early warning, and automatic driving.

2.1 Efficiency-Oriented Applications

Traffic forecasting and resource scheduling are complex tasks, which means that traditional machine learning methods often fail to extract the correct or enough spatial and temporal features to support predictions. **Graph neural networks** (**GNNs**), however, can be used to deal with complex, non-linear data structures [70, 106, 116]. Hence, many researchers are turning to these techniques. To date, GNNs have been used to analyze problems with traffic forecasting, resource scheduling, resource allocation efficiency, waste reduction, and energy consumption [14, 17, 18, 41, 57, 121, 135, 153, 170].

GNN uses in traffic forecasting: Timely and accurate traffic forecasting is crucial because it provides drivers and route planners with accurate navigation, scheduling, and flow control, which is the very basis of an intelligent transportation system. Traffic forecasting means to predict future traffic flows in terms of speed, volume, and/or density [33, 75, 134, 148, 154]. Forecasts can be short-term (5–30 min) or medium-to-long term (over 30 min). Medium-to-long term forecasts fall into two main categories: dynamic modeling and data-driven methods.

Dynamic modeling uses differential equations and physical knowledge to describe simulations of traffic problems. For this reason, dynamic modeling typically rests on an enormous amount of programming and consumes a significant amount of computing power. Importantly, invalid assumptions can significantly reduce the accuracy of predictions, so solid reasoning and meticulous rigor are essential with this type of forecasting.

Data-driven methods mostly rely on machine learning techniques, which make predictions about traffic. For example, Li et al. [63] developed a **diffusion convolutional recurrent neural network** (**DCRNN**), driven by machine learning, that regards traffic flow as a diffusion process on a directed graph. DCRNNs calculate spatial correlations via bidirectional random walks on a graph. An encoder-decoder architecture with scheduled sampling then captures temporal correlation to improve prediction accuracy. Any data available for collection is represented as weighted graph $g = (n, e, W)$, where n is a set of graph nodes, e is a set of graph edges, and W is a weight matrix. Formally, let X represent the graph signal of traffic flow, which is observed on g. The traffic flow obtained on g is represented by X, and $X^{(t)}$ is the graph signal obtained at time t. The goal of the prediction exercise is to derive a function $f(\cdot)$ that maps the historical graph signals N' to future graph signals N, given a graph g:

$$\left[\boldsymbol{X}^{(t-N'+1)}, \ldots, \boldsymbol{X}^{(t)}; \}\right] \xrightarrow{f(\cdot)} \left[\boldsymbol{X}^{(t+1)}, \ldots, \boldsymbol{X}^{(t+N)}\right]. \tag{1}$$

Bing Yu et al.'s [147] solution to predicting traffic flow involved a deep learning framework based on a **spatio-temporal graph convolution network** (**STGCN**). The task is set out on a graph, and the model is constructed through a full convolution structure, resulting in an approach that is very fast to train and requires fewer parameters than other convolution networks. As illustrated in Figure 1, the data in the STGCN $\mathcal{V}_t$ can be either a directed or an undirected graph, with or without a weight $\mathcal{W}_{ij}$, that is divided into frames. Each frame shows the traffic status $\boldsymbol{a}_t$ at a timestep t.

The application of GNNs in resource scheduling: Vehicle demand forecasting can help cities pre-allocate resources to meet their citizens' travel needs while also minimizing wasted resources.

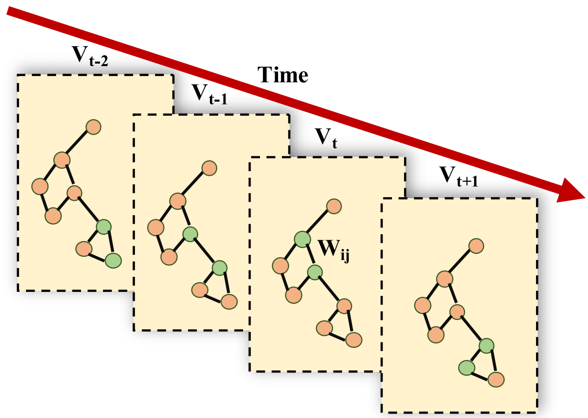

Fig. 1. Graph-structured traffic data.

With the growing popularity of vehicle and bike sharing, accurately predicting market demands is becoming more important.

Traditional demand forecasting for vehicles mainly depends on time series [115, 157, 158] forecasting. However, modeling complex data with non-linear time-space relationships is not feasible with this approach. Hence, Huaxiu Yao et al. [144] designed a **deep multi-view spatial-temporal network** (**DMVST-Net**) framework that jointly considers spatial, temporal, and semantic relations. The DMVST-Net constructs a regional map of vehicle demand based on the similarity of demand patterns, then makes predictions about the number of taxis that will be needed in various locations within a given time interval. To better manage bike-sharing systems, Chai et al. [22] presented a new multi-graph CNN to predict bike demand at the station level. In the model, the nodes of the graph are stations and the edge reflects a relationship between stations, e.g., where a bike may be picked up from one station and dropped off at another. Multiple graphs are constructed to reflect heterogeneous relationships, such as vehicle distance, driving record correlation, and so on. Lin et al. [65], similarly, introduced a data-driven, graph-based CNN model that forecasts bike demands at the station level on an hourly basis. This work was particularly impressive because the bike-sharing network discussed was very large-scale and many of the relations between stations were hidden, and so needed to be extracted.

2.2 Safety-Oriented Applications

Most applications concerned with making vehicle operations safer involve some form of data transmission—whether about the prevailing traffic conditions or the behavior of the driver or vehicle. Many safety applications are designed to work in IoT environments. Therefore, the section begins with a discussion on these types of applications before moving on to other types of safety applications.

2.2.1 Safety Applications for IoT Environments. As the number of vehicles on the streets has increased, so too has public attention toward driving safety. Several IoT sensor devices [54, 95, 118, 155] have been developed to resolve unsafe driving behaviors, such sensors that analyze the way a driver operates their vehicle and then provide feedback to help drivers change problematic behavior.

Drunk, drowsy, and distracted driving are the main causes of traffic accidents. To combat these three behaviors, algorithms have been used to assess driver behavior as they drive through in-vehicle perception technology. Such technology automatically evaluates and provides feedback to drivers, reducing traffic accidents. As powerful tools with rich internal sensors, smartphones can be used to detect all aspects of human behavior, including while driving. For example, Mariakakis et al. [81] use a **support vector machine** (**SVM**) coupled with smartphones that collect data from a driver's smartwatch to predict and prevent drunk driving. Similarly, Xie et al. [138] proposed a drowsy driving detection system called D^3 guard, which uses acoustic sensors embedded in smartphones to detect when a driver may be tired. More specifically, the sensors look for Doppler shift effects known to be caused by nodding, yawning, and operating the steering wheel in particular ways, then D^3 guard uses that data plus an LSTM neural network to build a personalized drowsy driving detector based on the driver's unique habits. Hong et al. [45], too, built a sensing platform based on smartphones and cheap sensors. Their model identifies aggressive driving by collecting data on vehicle speed, acceleration, deceleration, and steering wheel movements.

2.2.2 Other Safety Applications. Other safety applications include precise positioning systems, intersection management, cooperative adaptive cruise control, early warning systems, and emergency message broadcasting, among others.

Vehicle positioning applications [58, 60, 79, 101] can locate a vehicle in real time and reflect its trajectory on an electronic map. However, one familiar and frequently used backbone to these applications, GPS, has many disadvantages, including blind spots, unstable satellite signals, and poor accuracy. As a result, contemporary position applications combine GPS with a VANET for much more precise positioning. Interestingly, traffic lights are often used as noise reference points to increase the accuracy of GPS positioning. Pedestrian detection is a related technology, which commonly includes further integrations of vehicular radar or on-board cameras.

Given its role in reducing traffic congestion and accidents, intersection management has become a hot topic of research in the field of VANETs. Intersections are the main places where traffic congestion and traffic accidents occur and, at present, most intersections are governed by traffic lights with fixed timing controls. Lights change from red to green and back again as they were programmed no matter the present traffic conditions. The result is often congestion and low vehicle throughput. However, once all vehicles are able to exchange data on their speed, locations, and other motion states through V2I or V2V communications, VANETs will be able to govern extremely high throughput intersections. Further, once autonomous vehicles become the only cars on the road, traffic lights will not even be needed [32, 61, 82, 132, 149, 163]. Liu et al. [69] proposed a cooperative scheduling mechanism for intersections called TP-AIM. TP-AIM collects information about the surrounding vehicles, assigns the appropriate priority for all vehicles present, and plans an optimal route to the specified destination to ensure safety and reduce latency. Similarly, Wu et al. [133] proposed an autonomous intersection management system to replace conventional traffic control strategies. The system models vehicles that are driving through the intersection as sequences in a multi-agent Markov decision process. In this way, vehicles collaborate to move through the intersection, without colliding, in a way that minimizes delays. Note that the communication and computation technologies of automated vehicles are a necessary part of the framework. Cheng et al. [26] devised a system based on deploying a controller at the intersection. The controller divides all the vehicles in one lane into priority groups according to information exchanged with the vehicle and a fuzzy neural network grouping mechanism. Instructions to pass through the intersection are dispatched to each group of vehicles in turn via WiFi. This approach not only reduces vehicle waiting times and reduces congestion, but also provides a fairer passage through intersections. Improving traffic efficiency with schemes for intelligent intersections such as this is one of the most important aspects of traffic management.

Cooperative adaptive cruise control, or **CACC** for short, is basically a networked form of cruise control [56, 108, 113, 159, 164]. CACC has the potential to address many of the safety, stability, and fuel consumption problems of our current transport systems and, for this reason, it has been given much attention over the last decade. In normal cruise control, the driver sets the vehicle's speed and the system automatically maintains that speed by braking and accelerating as needed [8, 31, 78, 97]. However, with CACC, the vehicles form a platoon and travel at a coordinated speed. The vehicles are generally equipped with radar sensors to measure their distance from other vehicles, and they are used to collect and share information about surrounding vehicles via V2V. Gao et al. [37] extended adaptive cruise control with a scheme called **distributed adaptive sliding mode control** (**DASMC**). DASMC allows vehicles to interact with other surrounding vehicles using different eigenvalue-bounded topologies. To improve highway safety and throughput, Amoozadeh et al. [11] suggested a novel CACC system that follows a split, leader leaves, and follower leaves strategy. Their system can also retransmit messages to improve stability when communication fails. He et al. [44] proposed a Pareto-based framework to optimize energy management in CACC applications for hybrid electric vehicles. The method finds an optimal balance between the multiple objectives of energy efficiency, vehicle stability, and safety. To improve the stability of existing CACC strategies, Gong et al. [38] proposed an adaptive **proportional-derivative** (**PD**) controller. The scheme limits the impact of communication failures and, if communications do fail, the PD controller automatically switches to another type of CACC without exiting the original CACC, thus further increasing the system's stability.

Early warning systems span a number of needs, from warnings of inclement environmental conditions to vehicle faults to collision prevention. Early warning systems based on VANETs and machine learning to detect imminent collisions largely maintain the safety of vehicles and pedestrians by gathering information through V2V communications. However, these systems also frequently incorporate sensor technology, such as lasers, radar, cameras, and other types of optical sensors [122, 143, 169]. V2V communications is also integral to CACC, assistance with changing lanes or confluence, and glare reduction.

2.2.3 Emergency Message Broadcasting. Emergency message broadcasting [5, 28, 67, 68, 110, 150] is the basis of national safety systems and VANET safety applications alike. It involves quickly and reliably broadcasting information about danger to nearby vehicles, while allowing enough reaction time to take adequate measures to avoid an incident. However, given the stability issues that plague VANETs, transmitting emergency messages to relevant vehicles with surety can be problematic. The most common and reliable workaround is to broadcast black burst frames, which is a particular kind of analog signal often used as a reference signal to synchronize video equipment. This method divides the communication range into segments by sending black-burst interference frames. A number of different partitioning methods are available, including **binary partition assisted broadcast** (**BPAB**), **trinary partitioned black-burst based broadcast** protocol (**3P3B**), and **Huffman average** coding-based broadcast protocol (**HFMAVG**). Among the benefits of black-burst broadcasts, they require no additional infrastructure, and they can identify unique forwarding relay vehicles, message redundancy is reduced, and improves the employment of VANETs' channels.

Naturally, transmission speeds are a vital indicator of a good emergency message broadcasting scheme. The faster the speed, the sooner vehicles will receive the information, and the more time they will have to react [64]. However, without clear reference in the literature, we compared the transmission speeds of the three most common emergency message broadcasting protocols—BPAB, 3P3B, and HFMAVG—in a simulated environment built using the Veins framework. The scenario involved a SUMO mobile network running the 802.11p protocol. In the experiment, we

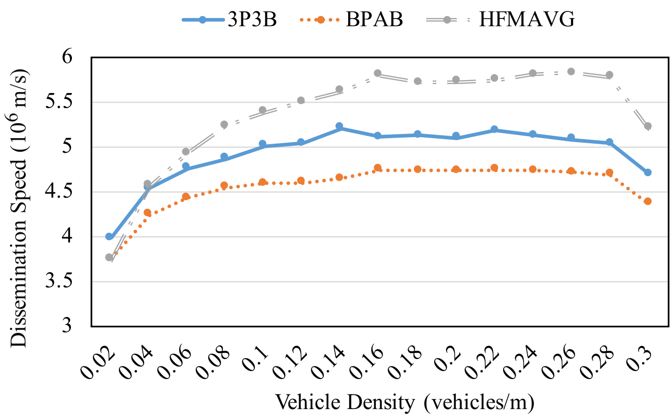

Fig. 2. Transmission speed on the 3,200 m, two-lane road.

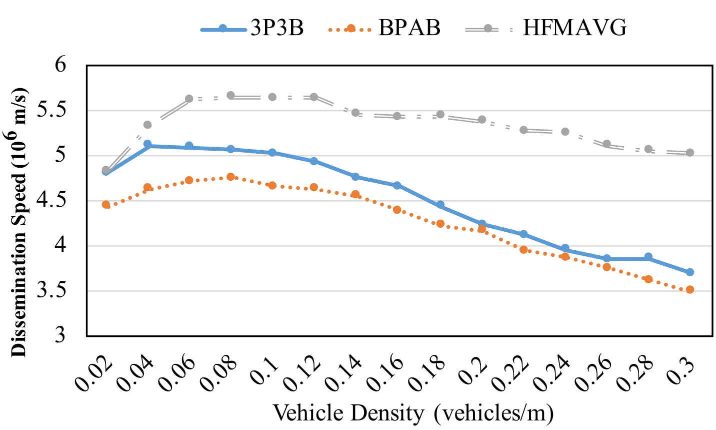

Fig. 3. Transmission speed on the 2000 m, six-lane road.

placed two roads: one that was 3.2 km long with two lanes, and another 2 km long with six lanes. We then set the maximum vehicle density of passing vehicles per lane to $n = 0.3$, which matches the standard capacity of a general urban road at less than 1,100 vehicles per hour. With these parameters in place, we analyzed the speed of message transmissions given different protocols and $n \in (0, 0.3)$.

The results of this experiment are shown in Figures 2 and 3. The horizontal coordinates represent the density of the lanes and the vertical coordinates chart the average transmission speeds of the emergency message. As shown in Figure 2, messages traveled fastest on the two-lane road at a density of 0.16. The average propagation velocities were 3P3B: 4.95×10^6 m/s; BPAB: 4.58×10^6 m/s; and HFMAVG: 5.4×10^6 m/s. Figure 3 shows that, on a six-lane road, transmission speeds peaked at a density of 0.08. The average speeds for each protocol were 3P3B: 4.51×10^6 m/s, BPAB: 4.26×10^6 m/s; and Huffman: 5.34×10^6 m/s.

According to these results, black-burst transmission speeds decrease as the number of lanes increase. Notably, advances in 5G communications may see improvements in the timeliness and reliability of emergency message broadcasting.

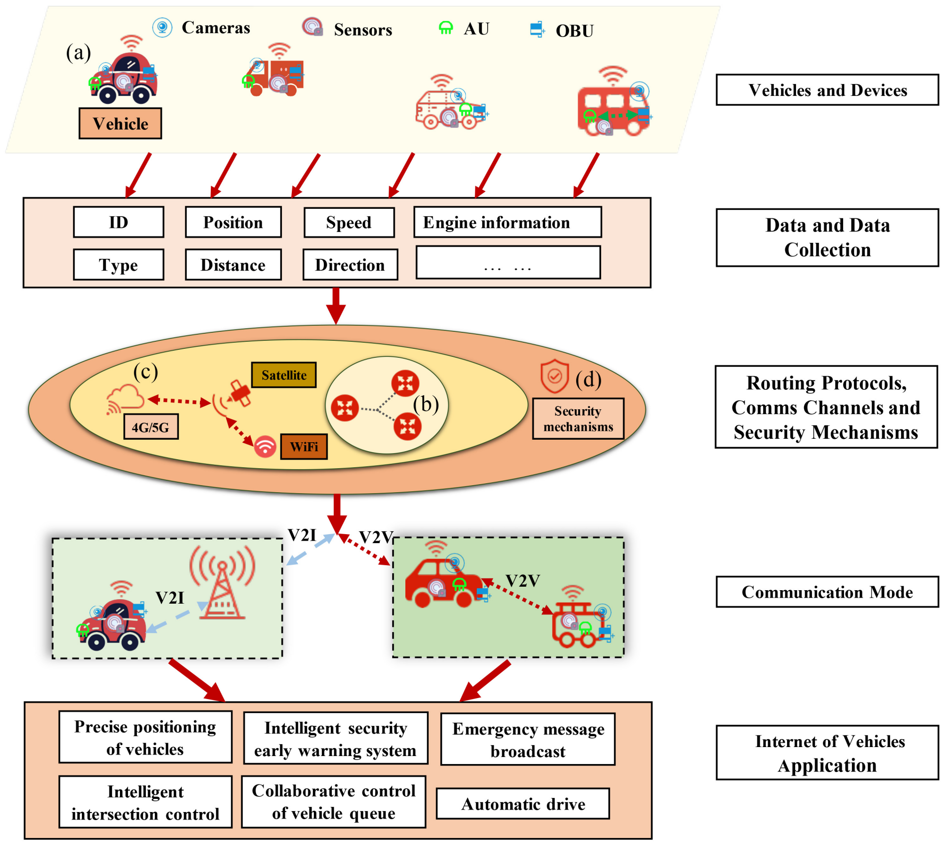

Fig. 4. The architecture of a typical VANET: Vehicles are equipped with application and on-board units, cameras, sensors, and/or other devices that collect road and traffic information, such as the IDs, types, positions, distances, and so forth, of other vehicles. These data are then transmitted to the other vehicles as well as to network applications to improve vehicle safety and efficiency. More specifically: (a) devices on the vehicles collect data; (b) these data are transmitted to other vehicles according to routing protocols; (c) transmissions are sent through 4G/5G broadband, satellite internet, WiFi, and so forth. Data exchange between vehicles is referred to as V2V communications, and exchanges between vehicles and infrastructure are referred to as V2I communications. (d) Network security protocols surrounding data transmission protect the security and integrity of the data and the system.

3 RESEARCH AND DEVELOPMENT INTO KEY VANETS TECHNOLOGIES

Like its applications, the key technologies surrounding VANETs support its goals of improving efficiency in urban transportation systems, reducing the incidence of traffic accidents, and reducing energy consumption. Further, VANETs will be foundational to the smart city of tomorrow. As shown in Figure 4, the main components of a VANET include vehicle information collection [112], data transmission [1], routing protocols [51, 85], security mechanisms [59, 77, 88, 90], and practical applications, or services [21, 103, 152]. Application, on-board, and roadside units commonly comprise GPS, radars, cameras, and sensors. After acquiring vehicle information, these entities use 4G/5G, satellite Internet and ZigBee to exchange data following the appropriate routing protocols via either V2V or V2I communication.

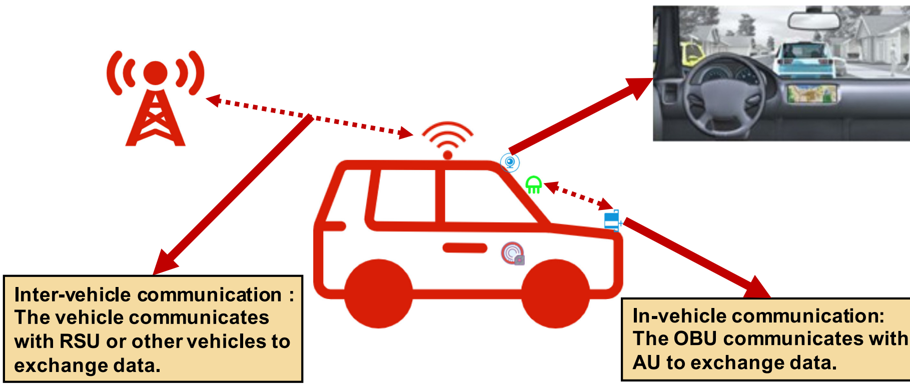

Fig. 5. Inter-vehicle communications: Vehicles exchange data with other vehicles or a roadside unit.

3.1 Information Collection

Information about a vehicle's status can be gathered through application units, on-board units, road-side units, cameras, sensors, GPS devices, radar, and so forth. Once gathered, the data are sent to their destination via a routing protocol [34]. There are two categories of data exchange: in-vehicle and inter-vehicle. In-vehicle communication concerns the data a vehicle gathers about itself, such as the vehicle's own position and speed. This type of data is generally transmitted to a safe or efficient application. Inter-vehicle data pertains to road traffic information and is most commonly used to assist with collision avoidance, passing assistance, and platooning [50]. A diagram showing the various types of information exchange is provided in Figure 5. In either V2V or V2I communications, data can be exchanged via 4G, 5G, satellite internet, a roadside unit, and so forth.

Vehicle position tracking is mostly handled by GPS in conjunction with the VANET. Relevant data about the vehicle's position in three-dimensional space, plus its direction, speed, and the time are conveyed in a short message from a satellite and displayed on a map. Although GPS does not work indoors or in tunnels, and it is prone to errors, its low cost, established infrastructure, and global coverage still make it the first choice for vehicle positioning.

To increase the accuracy of GPS and overcome blind spots, VANETs can use roadside units, radar detectors, and cameras installed on the vehicle in tandem with GPS. Radar can be used to detect targets, and calculate distances and velocities for obstacle discovery, collision prediction, adaptive cruise control, and reversing assistance. The signal return times are processed using the beam to encounter the obstacle back measurement and high-precision maps are generated to reflect the characteristics of the surrounding environment. With the advantages of real-time, high precision, strong resistance to environmental interference, high security, and adaptability to all-day climate change, radar is an essential supplement to GPS and sensors and a critical element of autonomous driving.

Sensors may be, arguably, the most accessible and convenient way to collect accurate and reliable information. Sensors can be internal or external to a vehicle. They can also be equipped to roadside units. Vehicle sensors can collect information on factors such as a vehicle's speed, distance traveled, distance to objects, pressure, temperature, and other engine indicators, as well as providing drivers with information about the current conditions surrounding the vehicle. Sensors also play an integral role in many safety applications, especially collision avoidance and autonomous driving. Internal sensors are typically used to detect engine temperature, oil pressure, battery, fuel consumption, and so on, while the main purpose of external sensors is to gather information about traffic and weather conditions, other vehicles, and pedestrians. External sensors often measure indicators like temperature, pressure, speed, energy consumption, acceleration, and radiation. Many sensors combined can provide a holistic picture of the drivers, vehicles, and environmental conditions of an entire transportation system. Hence, sensors have played a key role in the development of VANETs.

Application units are devices that provide services and can communicate with on-board units. They might be a user device, like a smartphone or tablet, that draws from one or more on-board units to provide a service, such as emergency vehicle warnings. Some applications, such as collision avoidance application, package the application unit and the on-board unit together in one physical unit. The application unit provides the services and the on-board unit manages all communication functions and liaises with the network.

On-board units are communication devices, designed for short-distance communication following the WAVE standard. A unique property of on-board units is that they can spontaneously form a self-organizing network to exchange information between vehicles without the need for other infrastructure [137]. On-board units generally consist of a GPS, a communications unit, sensors, and an audio and video processing module. Because communication can only occur over short distances, vehicles are, all at once, transmitters, receivers, relays, and routers, transmitting packets of data through a forwarding mechanism. The strategy provides for highly accurate vehicle positioning information over long distances and supports two-way V2V and V2I communication. This system can also broadcast information such as a vehicle's speed and acceleration, provide services for vehicle platooning and CACC, and play a role in vehicle security and early warning systems, auxiliary systems. As with most VANET elements, on-board units are also key to autonomous driving.

Roadside units are the single biggest contributor to improving VANET stability and expanding their data transmission range. In a sea of high-speed, frequently shifting network entities, roadside units are a fixed anchor for nearby vehicles to access many different kinds of communications and networking services. Roadside units are a type of network device, specifically designed for short-distance communications using the 802.11P protocol. They can serve as routers, data buffers, and servers; they can also provide or relay various types of information to vehicles on the road. Roadside units are a crucial component of VANET services like traffic and accident warnings, emergency messaging services, and electronic tolling.

3.2 Wireless Access Technology

In their current implementations, many wireless access technologies are simply used to provide the wireless interfaces needed for vehicles for V2I, V2V, and D2D communications. These modes of communication form the basis of all network cooperation. The main different types of wireless access technology include mobile network access, vehicle network access, and short-range communications, as shown in Figure 6, and the main network technologies are mobile (cellular) networks, WiFi, WiMAX (world interoperability for microwave access), Bluetooth, ZigBee, and **DSRC** (**dedicated short-range communications**). Of these, cellular networks, WiFi, and WiMAX depend on centralized infrastructure to coordinate communication between nodes, while Bluetooth, Zigbee, and DSRC use a distributed coordination mode to communicate.

3.2.1 Mobile Networks. Perhaps better known as 2G, 3G, 4G, and 5G, a mobile network is a hardware architecture for mobile communications. Mobile networks usually consist of a mobile station, a base station subsystem, and a network subsystem, which together provide many advantages, such as frequency reuse, wide transmission range, strong reliability, and high security. WiMAX is a high-speed wireless data network standard based on IEEE 802.16 that is mainly used

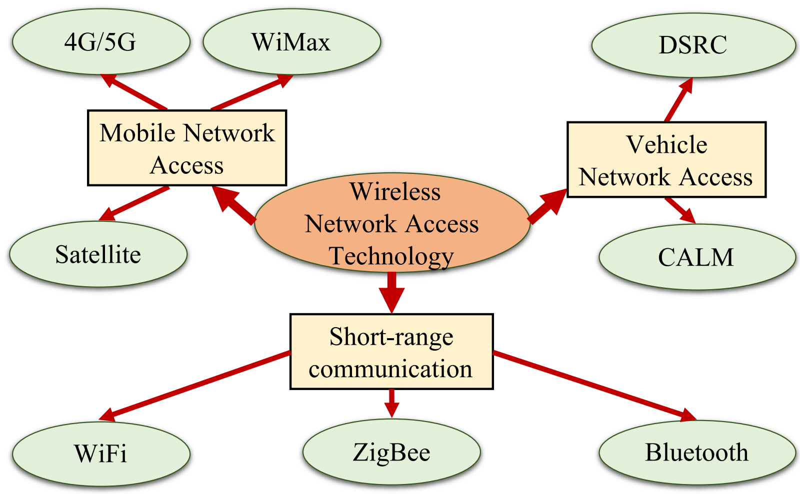

Fig. 6. The different types of wireless network technologies.

in urban area networks. Its advantages include a high data transmission rate, a wider transmission distance, better reliability, and wider bandwidth for higher quality communication. WiMAX can transmit at up to 35 Mbps over 15 km, and so is mainly used for multimedia, video, and language applications. Satellite internet combines satellite communication with optical fibers on the ground to provide wireless access for either V2I or V2V. With downstream data speeds of up to 506 Mbit/s and a communication range of between 100 m and 6,000 km, satellite internet access enjoys a broad coverage area and high reliability, making this access technology good for expanding the transmission range of a VANET or providing VANET services for remote villages. However, its disadvantages can include long transmission delays, high construction costs, and the need for complex control systems.

3.2.2 Vehicle Networks. Network communications can be sent through a wide range of schemes, such as mobile terminals or wireless local area networks. DSRC is an on-board communications technology based on IEEE 802.11p that supports vehicles moving at speeds of up to 200 Km/h with a range of 300 m–1,000 m. Data rates can exceed 27 Mbps. The advantages of DSRC include mobility support and low communication delays. Continuous Air-interface, Long and Medium range, or CALM for short, is a standard for networking within the ISO TC204/WG16 suite of guidelines. CALM stipulates a frequency of 5.9 GHz for seamless connectivity between vehicles and roadside systems.

3.2.3 Short-Range Communications. WiFi, also known as WLAN, follows the IEEE 802.11a standard for wireless network connections at a frequency of 5 GHz. Supporting data transmission rates of up to 54 Mbps and a communications range of between 30 m and 140 m, WiFi can be used for either V2I or V2V. It has a wider bandwidth, stronger RF signals, and lower power consumption than other access technologies, but its disadvantages are low security and a limited transmission range.

ZigBee is a close proximity ad hoc wireless network based on IEEE 802.15.4 that is used to transmit sensor data in VANETs. Zigbee can also estimate the position coordinates of vehicles in a VANET. Its communication range is in the order of 10 m–100 m, and the data rate is 250 kbit/s. It is highly secure, has low power consumption, and is cost-effective. But its short transmission distance and low data transmission rates are disadvantages.

Table 1. The Optimal Wireless Protocols for Different Types of Applications in a VANET

Application Type	**Example Services**	**Optimal Wireless Access Technology**	**Technical Requirements**
Preventive	Lane change assistance Adaptive cruise Misalignment warning	DSRC	Low delay High stability Data transfer rate
Warning	Automatic braking, emergency Electronic braking Dangerous location notification	DSRC	Low delay High stability Data transfer rate
Navigation	Real-time traffic information Parking space search Vehicle location	DSRC	Mobile support Privacy protection
Teleservice	Remote locking Vehicle diagnosis Notification of interest points	4G/5G	Long communication range High data transmission rate Scalability
Entertainment	Music download Online radio Location sharing	WiFi	Data transmission rate Mobile support Scalability

Bluetooth is another widely used standard for short-range communications. A consumer-oriented protocol, Bluetooth is often used for in-vehicle communications, such as navigating via GPS, streaming services, or allowing phone calls via the in-car interface. Its operating range is 10 m–100 m, and its connection speeds can reach up to 24 Mbps. Bluetooth is low-cost, easy to deploy, and is very robust to interference. However, it only operates over short distances and it suffers greatly from incompatibility issues, which makes it a poor tool for network-building.

These communication technologies differ in data rates, communication ranges, mobile support, communication latency, security support, and scalability. Hence, application developers must be careful to match the technical characteristics of the wireless access technology used for the service requirements of the application. Table 1 shows the best type of wireless network to use for different types of applications. Safety applications, such as lane change assistance, adaptive cruise, and warning applications like emergency electronic brakes and hazard location alerts can improve driving safety, but they require low latency and a stable data transmission rate. For this reason, DSRC is usually preferred. DSRC is also preferred for navigation applications, such as parking space searching and vehicle positioning, which both require high privacy protection. For remote services involving vehicle diagnosis and point of interest notification, 4G/5G or other mobile networks are the common options. For music downloads, online radio, and other entertainment apps, which tend to be data-intensive, WiFi is usually chosen.

3.3 Routing Protocols

As mentioned, vehicles move means VANETs topologies change frequently and rapidly, and communications and data exchange across the network is notoriously unstable as a result. Hence, methods to ensure reliable, real-time exchanges between vehicles have been the focus of many studies. Among the solutions, effective routing protocols are a key contributor to improving the speed and reliability of data transmission in VANETs [100, 102, 124].

Table 2. The Comparison of VANETs Routing Protocols

Protocol	Objective	Forwarding Decision	Map-Based	Delay Tolerant	Network Type	Classification Criteria
GSR	Minimize delay	Source-route, greedy	Yes	No	V2V	Geographic information
IDTAR	Minimize delay	Source-route	Yes	No	V2V	Geographic information
LBRP	Minimize delay	Source-route	Yes	No	V2I, V2V	Position-based
ESRA-MD	Minimize delay	Table-based	No	No	V2I	Geographic information
PassCAR	Improve stability, minimize delay	Table-based	No	No	V2V	Cluster-based
CBLTR	Improve stability	Table-based	No	Yes	V2V	Cluster-based
CCRM	Improve stability	Table-based	No	Yes	V2I	Cluster-based
GPSR	Shortest distance	Table-based	No		V2I, V2V	Greedy-based
GNGR	Minimize delay, improve stability	Table-based	No	No	V2I, V2V	Greedy-based
TGF	Minimize delay	Table-based	No	No	V2I, V2V	Greedy-based
BTSC	Improve stability	Source-route	Yes	Yes	V2V	Bus-based
Velar	Minimize delay	Source-route	Yes	Yes	V2V	Bus-based
GeoMob	Minimize delay	Source-route	Yes	No	V2I, V2V	Bus-based
PROPHET	Minimize delay	Source-route	No	Yes	V2I, V2V	Greedy-based
CAREFOR	Minimize delay	Source-route, greedy	No	Yes	V2I, V2V	Greedy-based
MOPR	Improve stability	Table-based	Yes	No	V2V	Link stability-based
VHRP	Improve stability	Table-based	No	No	V2I, V2V	Link stability-based

In reviewing the literature, we find routing protocols have been classified according to many different factors. However, the majority base their categories on the topological structure and types of information considered in routing decisions. Wang et al. [117] divide routing protocols this way into those based on topology, location, cluster, broadcast, and geography. Zheng et al. [166], however, propose a more comprehensive classification system based on whether the communication is V2V or V2I. In this article, we have based our classifications on the routing policy and method of data propagation. Table 2 presents a summary of representative protocols.

3.3.1 Policy-Based Protocols. The main types of policy-based routing strategies are based on location, clustering, or greedy algorithms, as shown in Figure 7.

Location-based protocols: Location-based routing protocols use a vehicle's self-configuring positioning mechanism and GPS to determine its location from road maps. Then, suitable vehicles are selected for data forwarding according to that location to reduce delays and improve the stability of data exchange. The GSR protocol defines city intersections as vertices in a model and streets as edges, while the Dijkstra algorithm finds the shortest path through which to forward a message. In message forwarding, intermediate vehicles act as a local cache and carry data forward as a proxy for normal direct transmission [89]. The IDTAR protocol [3] selects the appropriate intersection

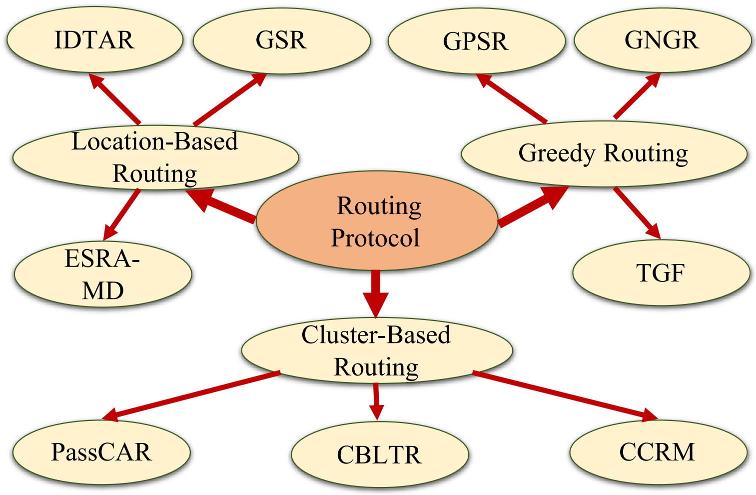

Fig. 7. Routing protocol classifications given different routing policies.

through which to transfer the data according to a vehicle density coefficient and the distance to the data packet destination, while the LBRP protocol developed by Hu et al. [46] is based on link lifecycle awareness for large-capacity content transmission. The vehicles make routing decisions about forwarding messages using a semi-Markov model that calculates transmission times and delays based on message headers, and the current speed and location of the vehicles in the network. Since vehicle movement is usually two-way and limited to the road infrastructure, any information directly relevant to location is of vital importance to decisions made in location-based routing protocols.

Cluster-based routing protocols: Routing protocols based on clustering group network nodes into a cluster according to some characteristic, such as node degree, lifecycle, the distance between nodes, and so forth. Throughput and stability are then improved by forwarding data based on the clustering partition and layering characteristics. For example, in the PassCAR protocol [13] a combination of the node degree, expected transmission quantity, and lifecycle of multi-metric selection strategy are applied to determine the cluster head, before forming a stable and reliable cluster structure for data forwarding. The CBLTR protocol [125] first defines the range of the cluster, before calculating the lifecycle of the vehicle according to the vehicle speed and the distance of the cluster boundary. The vehicle with the longest lifecycle is taken as the cluster head to improve the duration and stability of the connection. The CCRM routing protocol [62] divides vehicles into two groups: those with a relative distance of less than half the communication range and a trajectory of less than 45 degrees and connection time is less than threshold into a group, calculating to choose nodes with high stability and more connecting members as cluster heads. To maintain network topologies in a 5G network, the cluster heads are periodically exchanged with others on a membership list gathered together based on status information, base stations, and neighboring cluster heads. Overall, cluster-based routing protocols can simplify network topologies and improve throughput and stability. Moreover, they are suitable for large-scale network environments.

Greedy protocols: Routing protocols based on greedy algorithms construct the best path from the source node to the destination given distance, delay, location information, and other metrics. The GPSR routing algorithm, which uses a greedy forwarding algorithm to establish its route, is a typical example of a greedy routing protocol. With this protocol, the nearest node to the destination

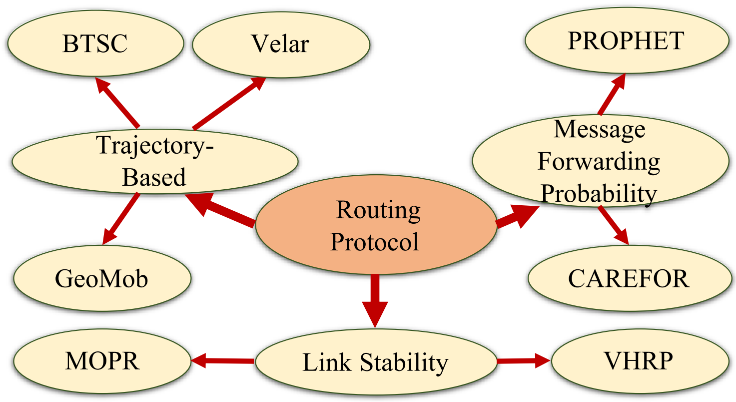

Fig. 8. Routing protocol classification given different data propagation.

node is selected as the next hop for routing and forwarding, and the process is repeated until all the data is transferred to the destination. GNGR greedy routing [9] searches for the shortest path from the node to the destination by forwarding packets to all nodes within transmission range. This serves to reduce data transmission delay and improve both the data transmission rates and the stability of the algorithm. The TGF routing protocol [47] searches for the farthest vehicle within communications range by sending data packets to all reachable nodes. It then uses the farthest vehicle as a relay node to reduce the number of hops and, in turn, delay between the source and destination. The TGF algorithm is simple to implement, fast to transmit, and it does not require too many control packages. In addition, it can improve network throughput, although it cannot guarantee the best overall performance.

3.3.2 Propagation-Based Protocols. Routing protocols based on data propagation use the road and bus routes information on maps to construct data transmission paths. In addition to improving communications efficiency and stability, this approach has the added benefit of reducing the cost of path recovery. Figure 8 shows the different types of propagation-based routing protocols. These include protocols based on vehicle trajectories, message forwarding probabilities, and link stability.

Vehicle trajectories: Buses are the most common form of public transport, with nearly every city and country in the world having some form of bus network, at least over its major traffic corridors. Hence, it makes sense to equip these buses with on-board units and use them to help route and relay data across the VANET. Sun et al. [104] developed a street center routing algorithm based on bus routes. The data routing maps are constructed by analyzing the probability of buses traveling each route. Buses along the selected route(s) are then chosen as relays to help transmit the data. Vela [151] also designed a routing protocol based on vehicle trajectories extracted from geolocation data. The framework mines the historical trajectories and travel times of buses as distributions, and uses that knowledge to predict actual traffic patterns given the same area and time of day. Routes are then propagated based on predicted actual running times and the probability of encounter. The GeoMob protocol [156] selects routes by analyzing the number of commuters between different regions coupled with the movement patterns of individual vehicles using geographic location information from smartphones. Paths with low predicted delays and high transmission rates are chosen. In fact, this is one of the key benefits of trajectory-based routing protocols. Because they incorporate existing vehicles and roadside units as data relays, this mode of routing is generally characterized by low transmission delays and high packet rates, making them suitable for urban traffic environments with large vehicle densities.

Message forwarding probability: Probability-based routing protocols are a recent but promising innovation. They use vehicle dynamics and co-location information, historical encounters with other vehicles, time-dependencies, plus the distance the message needs to be transmitted to estimate the probability that a message will be delivered. Co-location information includes the density of the vehicles and physical distance between neighboring vehicles. Unlike existing carry-forward mechanisms, message forwarding protocols use a predefined probability model to improve the overall performance of the VANET. Lindgren et al.'s [66] PROPHET protocol is one example. PROPHET, which stands for probabilistic routing protocol using history of encounters and transitivity, increases message delivery rates by selecting connected nodes with a higher (probabilistic) chance of transmitting the message to the final destination given the history of vehicle encounters and the transitive properties of the message. Mostafa et al. [87] introduced a novel probabilistic routing protocol called **CAREFOR** (**collision-aware reliable forwarding model**) that lowers packet forwarding collision by using a predefined probability to receive packets and rebroadcast those packets to neighboring nodes. To calculate the predefined probability, CAREFOR collates various environmental factors, such as vehicle density, transmission range, and the distance between the sender and receiver. The result is the probability that neighboring vehicles will receive a message and be able to rebroadcast it.

Link stability: This method improves link stability and consequently lowers the cost of path recovery, by using information about a vehicle's movement to predict the duration of a given path and find a new one before the link is disconnected. MOPR by Menouar et al. [84] is such a method. It improves the reactive routing process by assembling a routing table with information about the position, direction, speed, and street information of adjacent vehicles and constructing transmission routes based on forecasts given the information recorded. More specifically, the protocol calculates the lifetime of a link by searching the routing table for nodes in between the sender and receiver with similar speeds and directions. It then forecasts the future positions of those vehicles. Vehicles are included in the link based on their future position and estimated message transmission times. Taleb et al.'s [107] routing protocol, VHRP, groups vehicles according to their speed (and direction), on the premise that the groups of vehicles loosely traveling together will lend high stability. To reduce the risk of the link being interrupted if a vehicle leaves the current group, VHRP sends regular checks to make sure each vehicle is still with the pack.

4 THE CHALLENGES FACING VANETS

As a nascent, dynamic, and highly interdisciplinary field, there are still many challenges to address in the theory and application of VANETs.

4.1 General Challenges

The main theoretical challenges to overcome include weak network security, poor system reliability, a lack of global standards, and low intelligence levels.

4.1.1 Weak Network Security. The biggest and most urgent challenge facing VANETs is system security. As self-organizing mobile networks, VANETs are easy targets for hackers [77, 83, 145]. But a vulnerable VANET can place people's lives at risk or bring a city to its knees through gridlock. Thus, VANET security is a problem in need of urgent solutions.

The most common modes of attack [94] are location deception, denial of service, attacks on data integrity, and attacks on authentication and identification. For example, by masquerading as internal nodes, hackers can send error messages to nearby nodes to consume network bandwidth or spread false information about busy traffic to obscure or damage the topology of the network. Adversaries can also inject false information into data packets for a range of nefarious purposes.

The goal may be to infect neighboring vehicles which are currently acting as relays, or to change a routing table so as to direct a vehicle into an area without GPS coverage, making a real-world crime more difficult to trace [15, 48, 99, 114, 131, 141]. A brief description of each type of the main types of attack follows.

Location deception: Location information is of crucial importance in a VANET and, unfortunately, one of the easiest targets in a network to hack. Location deception consists of forging identities to provide false location information about a vehicle to its neighboring nodes. The idea is generally to use the fake position to cause a serious accident.

Denial of service (DoS): Arguably, DoS attacks are the most dangerous and vindictive class of attacks. The strategy is to bombard the system's communications channels with so much false information and transmission activity that service is completely disrupted for legitimate users. DoS attacks are usually system-wide, meaning they attack both the vehicles and the VANET infrastructure. As such, they are a fatal challenge to overcome.

Attacks on data integrity: Having data integrity means that the complete dataset arrives at its destination. Hence, attacks on data integrity include modifying, deleting, and adding vehicle information, usually with the objective of preventing vehicles from accessing application services. V2V communications are the most vulnerable to this kind of attack because an attacker can simply drop some data packets during transmission. Modifying a vehicle's sensors is also an option.

Attacks on authenticity and identification: Authenticity and identification are the first line of defense for VANETs. All terminals in a VANET should be authorized before accessing services. However, in authenticity and identification attacks, agents steal information by tampering, manufacturing, altering, masquerading as, and/or deleting vehicle identifiers. The only way to overcome this type of attack is to ensure that each vehicle in the VANET is authorized and certified.

4.1.2 Poor Reliability. As mentioned, the combination of moving objects and wireless communications in a self-organizing network inevitably makes the topological structures of VANETs unstable and unreliable. Further, vehicles move quickly, so network topologies change quickly, and interruptions are common as vehicles switch wireless connection points or try to talk to other vehicles that are no longer in the position they were. Communication paths typically have a very short lifetime, which affects network reliability. Another weakness in VANETs is that vehicle movements are constrained to the road, which rules out some of the traditional "re-routing" methods of improving stability. Section 3.3 on the routing protocols discussed some of the different approaches to stabilizing data transmission. However, to improve the reliability of the whole system, not just data exchange, transmission media, network recovery, and network management must all be considered.

4.1.3 A Lack of Uniform Standards. VANETs can make urban traffic safer, greener, and more efficient. However, for every vehicle, roadside unit, application unit, onboard unit, smartphone and so forth, to be able to connect, uniform international standards are required that all manufacturers and network designers must follow. VANETs need to be as universal as the internet. At present, two main camps are each for a different set of standards to become the norm. The US DoT supports DSRC, while China supports the LTE-V2X standard. DSRC is based on IEEE 802.11p and relies exclusively on radio frequencies to communicate. It supports real-time transmission of images, voice, and data information and recognizes high-speed moving targets in a specific area using two-way V2V or V2I communication. DSRC has the advantage of low latency and low interference, but it is only suitable for short-range communications. By comparison, the LTE-V2X standard relies on the existing mobile network and other infrastructure so it can handle both short-distance and wide-area communications. Its advantages include long-distance coverage, high capacity, high reliability, and low delay. However, due to its relative newness, the standards are still being revised and finessed. Whichever standard emerges as the victor, cooperation between countries and the support of international organizations will be needed to promote and advance the standards into a fully supported framework for VANET implementation. Further, as 5G communications technology matures, it will provide better support and more choices for the development of VANETs.

4.1.4 Low Intelligence Levels. Although scholars have been undertaking research into VANETs for years, relatively little work has been translated into applications and fully popularized. Network stability and interconnectivity have been major roadblocks to progress. However, so has a lack of basic data on intelligent vehicles. As a result, the intelligence levels of VANETs are rather low[71, 105, 109, 123, 142, 161]. There is little to no support for functions such as intelligent routing protocols, traffic forecasting, resource scheduling, malicious activity detection, or network management. The last two decades have seen incredible developments in artificial intelligence, image recognition, pattern recognition, natural language processing, and other similar technologies. These advances now need to be incorporated into VANETs. More on this issue is discussed in Section 5; however, the foreseeable future of VANET research is heavily bent toward meeting higher benchmarks for safety and efficiency by integrating intelligent technologies such as autonomous judgment and real-time decision-making.

4.2 Application Challenges

In keeping with our focus on safety and efficiency, this section is divided into the unique challenges application designers are facing in meeting these two objectives.

4.2.1 Safety. The biggest challenge facing safety-oriented applications is delays in transmission times. As a general rule, the faster one receives a warning, the more time one has to react, and the greater the chance of averting danger. Hence, safety applications are typically highly sensitive to time delays. Delays can be caused by many things, including changes in the topological structure of the VANET and long transmission distances. Solutions in the form of better coding or routing protocols have solved most of the existing problems with delay times. However, contemporary standards do not yet meet the performance required for emergency messaging. As 5G continues to develop, with its very low delay times and support for long-distance communications, integrating VANETs and 5G may change this situation.

4.2.2 Efficiency. Instilling efficiency is heavily dependent on data collection and, more specifically, on extracting as many features as possible from the data collected so as to maximize a model's prediction accuracy. Traditionally, data was described in Euclidean space and, while this conceptualization will continue to be commonplace, a growing number of applications are representing data in non-Euclidean terms, such as via complex graph structure. Prediction techniques for Euclidean space are well-established; we can use deep learning, support vector machine, XGBoost, and many other techniques, to build a precise prediction model. For graph data, however, the existing GNN methods are less developed. For example, it is not always easy to extract spatio-temporal data features from a graph. And directly applying current GNN techniques to heterogeneous graphs containing mixed data types and formats can be problematic. Further, graph structures may change in a way that makes it difficult for models to adapt.

5 FUTURE DIRECTIONS OF RESEARCH

Advancements in 5G, GNNs, reinforcement learning, deep learning and other future technologies are constantly providing new research directions for VANETs. 5G is showing promise as a way to improve the quality of service and the reliability of data transmissions, while machine learning is opening avenues for intelligent applications, adaptive network management, and securing networks. From our analysis of the current development trends in VANETs, in the future, researchers should pay attention to improving security, improving reliability, and raising intelligence, as discussed next.

5.1 Improving Security

VANETs are an immature innovation. As a result, they have low security and tend to be easy targets for hackers. The most common defense against adversaries is to protect or obscure the information in the system.

For example, to protect against location spoofing attacks, nodes can be encrypted with anonymous secret keys, pseudonyms, or group signatures [43, 140] that only trusted parties know. The Bayesian model may also be able to capture the characteristics of the attack by analyzing many attacks and automatically investigating and filtering malicious queries and wrong locations. Machine learning algorithms, such as decision trees, can help with this filtering process and may also be able to isolate the attacker and stop their spoof.

Intermediate attacks might be prevented through a cooperative message authentication mechanism. Such mechanisms allow vehicles to use public-key encryption and secret-key encryption to sign messages. Alternatively, roadside units, which can track vehicles, can be used to detect improper behavior by nodes via member authentication.

To cope with the information spoofing attacks of the destruction of hardware and software in VANETs, Wang et al. [119] have proposed a security framework based on group signatures. The framework can detect nodes that are tampering with software using access control methods and a probabilistic signature verification scheme. To prevent tampering with hardware, vehicle data are correlated and cross-validated through a series of rules. In this same vein, other security frameworks could be developed to protect VANET assets by checking functions like signature generation and verification, password authorizations, or firewall exceptions [119].

5.2 Improving Reliability

Improving network reliability will rest on better hardware and software designs. Hardware choices can reduce load capacities and node failures, making data exchange and processing a much more certain task. Software choices can lower delays and extend transmission ranges to the same end.

One promising hardware innovation is optical devices. Optical devices are cameras and lidar. They have excellent stability and so work to improve the reliability of network nodes and increase the network's capacity for data transmission. This is especially important because VANET applications can generate large amounts of structured and unstructured data.

Hardware architecture is another important element. Existing architectures comprising cellular networks, roadside units, and vehicles are not capable of handling scalable data efficiently. However, IoT-based edge and fog computing are some appealing strategies for overcoming this issue, especially when implemented in a distributed architecture that can support different services such as storage, computation, and communication between the vehicles.

Improving reliability through software will come from better routing protocols or by creating combined software/hardware solutions. For example, 5G enjoys high reliability and low latency, making it a dependable protocol for data transmission. Combining cloud platforms, such as Hadoop, Amazon's EC2, Alibaba Cloud, and Azure, to manage distributed hardware can improve reliability. Moreover, combining AI-driven routing protocols with 5G and a cloud platform can create an open and flexible system to support a variety of powerful safety and efficiency applications.

Table 3. Summary of Machine Learning Algorithms that Could Raise Intelligence in VANETs

Category	Task	Approach	Application
Supervised learning	Classification	Bayesian classifier	Vehicle location prediction; Network monitoring; Resource optimization; Link fault classification; Network error detection; Traffic classification
		Support vector machine	
		Neural networks	
		Binary decision tree	
	Regression	K-nearest neighbor	Traffic forecasting; Interest point notification; Vehicle status prediction
		Regression tree	
		LSTM	
		XGBoost	
Reinforcement learning	-	Value iteration	Real-time decisions; Skill acquisition; Personal driving assistant; Autonomous cars
		Policy iteration	
		Monte Carlo	
Unsupervised learning	Clustering	k-means	Recommendation system; System filtering; Network parameter configuration; Fault classification
		CNNs	
		DBNs	
	Generative adversarial networks	-	Malicious attack detection; Image generation
	Dimensionality reduction	Principal component analysis	Face recognition
Semi-supervised learning	Classification	GNNs	Traffic forecasting; Resource scheduling
		GCNs	
		RGNNs	

5.3 Raising Intelligence

Intelligent VANETs can improve vehicle safety, comfort, and energy efficiency—so VANET intelligence is a major trend area for future development. As shown in Table 3, there are many machine learning algorithms that could replace traditional algorithms to boost VANET intelligence. Machine learning algorithms can be divided into four main groups: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Each type of algorithm has its strengths and weaknesses and can be used to improve a different aspect of network intelligence or application service, as the last column in Table 3 shows [10]. In the following sections, we highlight four promising areas of future development that could significantly contribute to raising the intelligence capacity of VANETs.

Reinforcement learning: In the world of machine learning, improved accuracy and performance means gathering as much data as possible. However, in VANETs, these data are distributed between vehicles, application units, roadside units, base stations, cloud servers, and so on, and so cannot be used reliably. Reinforcement learning can aggregate data from the number of source nodes onto one destination node to provide a solid and sufficient dataset for a machine learning model [12, 24, 29, 76, 86, 92, 136].

The reinforcement learning tasks can be formalized as follows: Given a tuple $\mathrm{R}(S, A, \rho, f, R)$, where $S = \{s_1, s_2, s_3 \ldots s_t\}$ is the set of environmental states, and s_t is the state of the agent at time t; $\mathrm{A} = \{a_1, a_2, a_3 \ldots a_t\}$ represents a collection of actions, and a_t is the action taken by the agent at time t. ρ is a reward function for executing action a_t at state s_t, f is the probability distribution function of state transition, which represents the probability that the agent performs an action at the state s_t to transfer to the next state s_{t+1}, R is the reward value obtained by executing action a_t at state s_t. Reinforcement learning is the agent in the state s_t select action a_t. The agent then performs the action and transfers its state from s_t to the next state of the s_{t+1} with a certain probability f. The last step is to distribute feedback in the form of rewards R_t. Usually, the reward received in each timestep is multiplied by a discount factor $\gamma \in [0, 1]$. Hence, the formula for calculating the sum of obtained rewards received from time t to time T is

$$\text{Sum} = \sum_{i=t}^{T} R^{t-T} \gamma_i. \tag{2}$$

Inspired by recent successes in solving complex control problems through reinforcement learning techniques, we contend that reinforcement learning might also be used to solve routing problems in VANETs. The movements of vehicles could be predicted by employing deep reinforcement learning, from which a few routing paths with good transmission capacity could be chosen as "pilot routes." The idea would be to send packets down these routes to provide in-time routing information. Selecting the forwarding direction between vehicles according to the destination location and the estimated transmission delays in different directions may also help to lower transmission delay and improve stability.

Therefore, with the advantages of short training time, moderate data requirements, and high performance, reinforcement learning might be an excellent model for applications in the area of autonomous driving, real-time decision-making, congestion control, and intelligent routing.

GNNs: With the rapid development of VANETs, more and more applications are generating heterogeneous data. However, large-scale data are of little use without effective methods of feature extraction. GNNs are excellent at capturing temporal and spatial dependence while concurrently solving dynamic problems. Hence, a key component of future VANET research is highly likely to involve designing new GNN models.

Network traffic classification: Network traffic classification is the basis of network monitoring, quality of service, and intrusion detection, and is a task that would benefit substantially from advancements in machine learning [128–130]. Machine learning classifiers, such as Naive Bayes [126, 127], neural networks [160], and decision trees, could be used to automatically classify network traffic according to any of multiple criteria, e.g., the time interval between packet arrivals, packet size, cyclic traffic patterns, and so forth [36]. The lack of labeled traffic data currently prevents real-time classification with traditional machine learning techniques. However, there are many deep learning techniques that can learn features from raw data. The obstacle, therefore, becomes one of resources. Deep learning demands high-performance equipment, but the resources in VANETs tend to be quite limited. Hence, sleek and efficient deep learning models, specifically designed to operate on the scant resources of VANETs, will be much needed in the future.

Predicting states in VANETs: Perhaps one of the most significant functions that AI could perform in a VANET going forward is to predict the state of the vehicle. Traditional Bayesian models can predict the state of the next period according to the current characteristics and feature relationships. However, RNN [27, 162] -based deep learning [165], tree-based XGBoost [25, 91], and LSTM neural network [39, 72] can improve prediction accuracy to include characteristic dependencies across a relatively long period of time. For example, a deep neural network could be used to predict the target lane of a vehicle given the vehicle's status and lane information. These prediction models could also be used to assess future values or states based on past samples. An example mathematical representation might be

$$\hat{P} = F(A_t, \rho) + L(.,.), \tag{3}$$

where $\hat{P}$ is the prediction value based on the past historical state. $A_t = \{A_{t1}, A_{t2}, A_{t3}, \ldots, A_{tT}\}$ is a set of features extracted from historical data after data processing and ρ is the parameter set in the prediction model.

In the process of forecasting, the parameters of the model need to be continuously adjusted so that the prediction performance of the model achieves the best prediction accuracy. Here, $L(.,.)$ is a loss function, which is mainly used to assess the difference between the estimated values and the true values. The prediction model, based on sequential data, seeks to find a function F according to the prediction target. High prediction accuracy is achieved by continuously adjusting the parameter set ρ of the model according to the loss function and the feature set of the historical data.

This or a similar strategy may go a long way to offsetting the reliability and stability problems with VANETs. However, the only way to know is to undertake further study.

6 CONCLUSION

As an essential part of intelligent transport, VANETs have attracted increasing research attention in recent years. To offer the interested reader a comprehensive perspective on the existing research in the field, we have reviewed three main VANET research areas: typical applications, key technologies, and major challenges faced. To begin, we reviewed the safety and efficiency applications of VANETs and related technologies, focusing on GNNs, Reinforcement Learning (RL), 5G, and others. These technologies can significantly improve the safety and efficiency of vehicles. Additionally, we explored and compared information collection, routing algorithms, and emergency message broadcasting within VANETs. Finally, we discussed the limitations of VANETs in terms of network security, reliability, and intelligence, before elaborating on the challenges and future directions associated with intelligent VANETs. We highlighted VANET intelligence as a promising future research direction. In particular, researchers could consider how to tackle issues such as vehicle dynamics, computational resource consumption, and lack of extensive available data, to enhance VANET intelligence. Further, we argue that lightweight and efficient learning models are needed and should be a future research focus.

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