Systematic Literature Review of AI/ML Techniques applied to VANET Routing

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***Abstract*— Vehicular ad hoc networks (VANETs) have emerged as a powerful network model for providing road safety, as well as infotainment applications, for vehicle passengers and drivers alike. These networks are characterized by high node mobility, which in turn introduces communication intermittency and unreliability, deteriorating the network's performance. To provide solutions to the concerns of performance of such networks, articles have proposed intelligent approaches to deal with such issues by means of artificial intelligence and machine learning techniques. This study aimed to review the literature regarding intelligent routing protocols in VANETs by focusing on the techniques used and on how the solutions were evaluated based on performance. A systematic literature review of studies was conducted by adopting the snowballing procedure to collect studies that propose novel approaches to solving the VANET routing protocol by means of intelligent algorithms. The 86 included studies reported that heuristics, fuzzy logic systems and reinforcement learning approaches are the most popular and effective methods to improve network performance in the dynamic VANET environment. The findings have also shown that the literature has yet to find a consensus as to how to evaluate routing protocol performance. An evaluation and comparison framework is required as to enable transparent routing protocol design and selection in future vehicle applications.**

Keywords—Vehicular ad hoc networks, intelligent routing protocol, intelligent algorithms, data dissemination, systematic literature review

I. Introduction

As per the World Health Organization's (WHO) reports, approximately 1.35 million people die each year resulting of road accidents. It is estimated that between 20 and 50 million people fall victim to non-fatal injuries, with many developing into lifelong disabilities [1]. Recent studies have analyzed the impact of warning mechanisms on road accident prevention and presented sound evidence as to the importance of these systems in accomplishing the WHO's goal of reducing deaths and injuries in road accidents to 50% by 2030 [2]–[4]. Connected vehicle technologies are seen as a promising solution to prevent and mitigate road accidents by means of emergency message dissemination and information sharing through inter-vehicle communication [5], [6].

VANETs are a unique subset of the mobile ad hoc networks (MANETs) paradigm, and consists of having vehicles behaving as routers, forwarding messages to other vehicles, thus establishing a wireless ad hoc network. To achieve this, vehicles are equipped with wireless communication devices known as OBUs (on-board units). Communication can either be vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I), in which road-side units (RSUs) are distributed in the infrastructure and can be used to enhance communication and provide gateways for Internet access. These networks support the development of novel applications and solutions to real-world problems, such as road accident prevention, through accident detection and vehicle diagnosis, reduction of fuel and energy consumption, and congestion control [7].

MANETs are characterized by dynamic network topologies, with frequent topology changes, fluctuating capacity links, and network fragmentation, because of high node mobility. In VANETs these properties are further augmented due to the higher mobility of vehicles. These characteristics, while proving beneficial for the envisioned applications based on the ad hoc paradigm, pose an issue for data dissemination, data sharing, and security [8], deteriorating the reliability of routing paths. With most applications relying upon routing to successfully deliver messages across the network of vehicles, their performance may be severely impacted, with warning messages arriving too late to the destination vehicle to warn the driver of a possible hazard, or not arriving at all. In such environments, message delay and failure in delivery are inevitable, however, they can be mitigated by utilizing reliable routing protocols that attempt to provide the best degree of communications while consuming the least number of resources. Thus, optimal route selection and packet forwarding are critical challenges to the success of VANET applications. Several routing protocols have been proposed to address this issue in MANET environments, however, due to the differences in the speed and movement patterns between MANET and VANET nodes, most protocols have led to poor performances [8].

Artificial intelligence (AI) is described in [9] as the study of intelligent agents which perceive the environment and calculate the best actions to achieve a specific goal, while machine learning (ML) focuses on the study of algorithms and their capacity to continuously and automatically learn and improve their performance in solving certain tasks. Techniques in AI comprises heuristics, swarm intelligence (SI), game theoretic approaches, fuzzy logic systems, among others [10]. More recently, AI and ML have successfully been applied to fields such as healthcare [11], environmental systems modelling [12], and to improve communications in computer networking, with traffic prediction applications [13], network topology design [14] and routing in software-defined networking [15]. Due to the capability of AI/ML techniques to provide sound solutions in dynamic environments, they have been used in several studies to improve routing in VANETs.

The purpose of this study is to review the use of AI/ML techniques in the design of routing protocols for VANET environments. The paper's structure is organized as follows. Section II covers the proposed research questions and depicts the methodology used to perform the systematic literature review. Section III describes the snowballing procedure and presents the included papers. In section IV, the study's results are displayed and described. In section V, the research questions are answered, by critically analyzing the results and supporting them with the evidence found in the literature. We close the paper with section VI, by highlighting the main takeaways and future research prospects.

II. Methodology

Systematic literature reviews are important research studies that aim to cover a wide range of publications and compile their findings to provide answers to specific research questions. Through scrutinizing previous research works, research moves from specific questions pertaining to the aims of each study, to broader questions that may determine new research paths for future work. This study follows a systematic literature review procedure, based on the snowballing method which guidelines are presented by Wohlin in [16]. The remainder of this section describes the followed steps.

A. Research questions

The present study addresses the following research questions:

RQ1. How much activity has there been on the field recently?
RQ2. How are AI/ML-based VANET routing protocols taxonomically classified?
RQ3. What are the AI/ML techniques that have been used in improving the performance of the routing protocols?
RQ4. How is the performance of such protocols measured?

To address RQ1, we identified the number of articles published every year that introduce novel solutions to VANET routing by using AI/ML algorithms.

The aim of RQ2 is to identify the taxonomies of intelligent routing protocols to better grasp how AI/ML can be applied. The taxonomies were identified based on the way that protocols devise network topology, perform route selection, and forward data packets to next-hop routers. The traditional protocol types described by Singh et al. in [17] were also used as the basis for determining taxonomies in the present study.

RQ3 concerns which AI/ML techniques are most used in the VANET routing domain, comparing the effectiveness of different intelligent techniques and their respective advantages and disadvantages.

In respect to the RQ4, comparison and evaluation of the performance of the proposed protocols is a very important aspect to help future studies decide which protocol is the most suited to the VANET application in question.

B. Source and search string

As to avoid publisher bias, the Google Scholar database was chosen as the article search engine for the selection of the starting set. The search engine selects articles based on a given search string. Hence, the search string used must include the relevant terms for the intended research.

To construct the search string, "AI", "ML", "VANET" and "routing" were chosen as the main keywords. Related keywords and synonyms were identified based on a brief analysis of articles that include the main keywords (Table I). In respect to these terms, the following search string was considered:

("vehicular ad hoc network" OR "vanet" OR "intelligent transportation network" OR "intelligent transportation system" OR "vehicular network" OR "inter-vehicular network") AND "routing" AND ("artificial intelligence" OR "ai" OR "machine learning" OR "ml")

TABLE I. Search string keywords

Main keywords	Related keywords
VANET	Vehicular Ad Hoc Network Intelligent Transportation Network Intelligent Transportation System Vehicular Network Inter-vehicular Network
AI	Artificial Intelligence
ML	Machine Learning
Routing	

C. Inclusion and exclusion criteria

Primary articles that cover the topics of VANETs, data routing/dissemination, and AI/ML methods, were included. Secondary studies (i.e., surveys, reviews, overviews, and comparative analyses) were not considered for inclusion, since the focus of the study is to provide a systematic review over articles that propose original VANET routing protocols and solutions by using AI/ML techniques.

Articles that were not written in English, to which access has not been granted, or that are considered as an extension of previously analyzed works, were excluded.

D. Data collection

From each paper included as the result of the snowballing procedure, key information was extracted, namely: full reference; characteristics specific to each routing protocol, such as route selection method and the use of network segmentation; which AI/ML techniques were utilized; and which parameters were used in performance evaluation and protocol comparison.

E. Snowballing procedure

The search for papers to include in the study was conducted between November 26th, 2020, and January 30th, 2021.

An initial set of 15 candidate papers was assembled based on a Google scholar search using the presented search string. From these 15 candidates, initially 5 ([18], [19], [20], [21] and [22]) were excluded, based on not being allowed access. One candidate ([10]) was excluded based on being a secondary study. Four more candidates ([23], [24], [25] and [26]) were excluded, with two focusing on security challenges, one concerns vehicle routing instead of packet routing, and a fourth does not employing any AI/ML technique. The papers [27], [28], [29], [30] and [31] were included as the start set for the snowballing.

The first iteration of the snowballing process, considering the start set of the 5 chosen papers, resulted in the analysis of 135 papers for inclusion, of which only 14 were included, yielding an efficiency of 10.4%. Through the second iteration, 741 papers were analyzed, with 674 being excluded (of which 141 due to being either duplicates or extensions of previously analyzed works), thus culminating in the inclusion of 67 studies, and 9.0% efficiency.

In total, 891 papers were probed following the start set selection and the two performed iterations. Based on the defined criteria, 86 papers were found. The efficiency of the snowballing procedure conducted was of 9.7%. It is to be noted that a third iteration could be carried out, however, due to the sheer volume of research work found, the set of papers

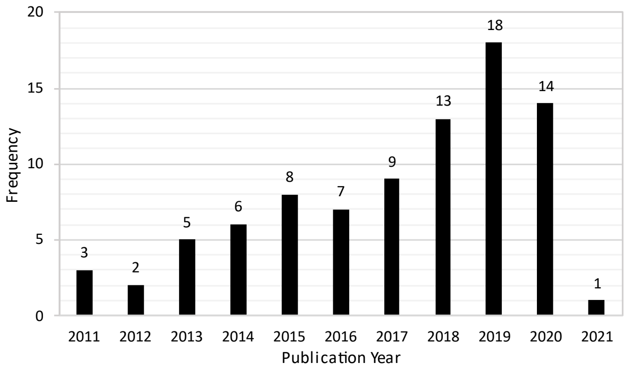


Fig. 1. Frequency of papers by publication year.

included in the study was considered as an appropriate representative set of current and past research on the application of AI/ML techniques to routing in VANETs.

III. Results

The results described in the present section were extracted from the 86 included articles. The raw data can be analyzed in full in [32].

Figure 1 presents the number of studies found by publication year. In 2011 and 2012 only two to three studies were found. These numbers increased, hitting a peak in 2019 with 18 included studies. In 2020 and 2021 the number of papers decreased.

Routing solutions differ in various aspects, such as in the manner in the information stored in the routing tables and on the nature of destination, which can be a single node or a group of associated nodes. Table II shows articles grouped according to the type of routing protocol. There are 28 papers that adhere to the topology-based protocol model, the most dominant class. There were 22 papers that presented solutions based on geography-based protocols, and 21 based on clustering protocols. The hybrid, multicast and geocast protocols represent six, five and four papers included. The three main protocols (i.e., topology, geography, and clustering-based protocols) correspond to 82.6% of the total number of papers considered.

The AI/ML techniques were grouped into four categories/classes, following the survey conducted in [10], namely: heuristic and SI approaches; ML algorithms; fuzzy logic systems; and game-theoretical approaches.

Regarding the heuristics and SI techniques, 17 papers were found to apply Ant Colony Optimization (ACO) to the VANET routing problem, 14 used the Particle Swarm Optimization (PSO) technique, and 11 employed a Genetic Algorithm (GA). There were 39 papers that used other less

TABLE II. Articles ordered by protocol type

Protocol Type	Articles
Topology	[27][28][29][30][36][37][38][39][40][41][42][43][44][45][46][47][48][49][50][51][52][53][54][55][56][57][58][59]
Geography	[60][61][62][63][64][65][66][67][16][68][69][70][71][72][73][74][75][76][77][78][79][80][81]
Clustering	[31][82][35][83][84][85][86][87][33][34][88][89][90][91][92][93][94][95][96][97][98]
Hybrid	[99][100][101][102][103][104]
Multicast	[105][106][107][108][109]
Geocast	[110][111][112][113]

TABLE III. Classes of AI/ML techniques used in the articles' proposed routing solutions

Classes of AI/ML Techniques		Articles
Heuristics & SI	ACO	[29][36][60][38][61][62][82][102][66][67][71][46][48][96][97] [57][104]
	PSO	[29][30][37][39][110][40][42][44][89][73][98][112][113][80]
	GA	[39][64][70][50][90][52][92][111][93][103][109]
	Others	[99][105][39][100][101][40][63][35][41][83][84][42][65][106][33][69][45][34][88][47][72][49][107][51][52][91][54][74][75][93][108][56][94][95][78][103][109][79][58]
ML	Supervised	[27][31][100][84][43][68]
	Unsupervised	[102][34][93]
	Reinforcement	[28][42][85][86][87][53][55][76][59]
	Transfer Learning	[53]
Fuzzy-Logic		[27][63][41][85][86][87][49][53][111][77][79][59][81]
Game Theory		[85]

popular methods, such as the Improved Whale Optimization [33], the Moth Flame Optimizer [34], and the Grasshopper Optimization Algorithm [35]. The ACO, PSO and GA techniques represent 51.85% of the heuristic and SI methods found.

The ML algorithms were divided among four classes: (i) supervised learning; (ii) unsupervised learning; (iii) reinforcement learning; and (iv) transfer learning. Supervised and unsupervised techniques were applied in six and three papers, respectively, while reinforcement learning techniques were implemented in nine papers. Only one paper was found to utilize a transfer learning algorithm.

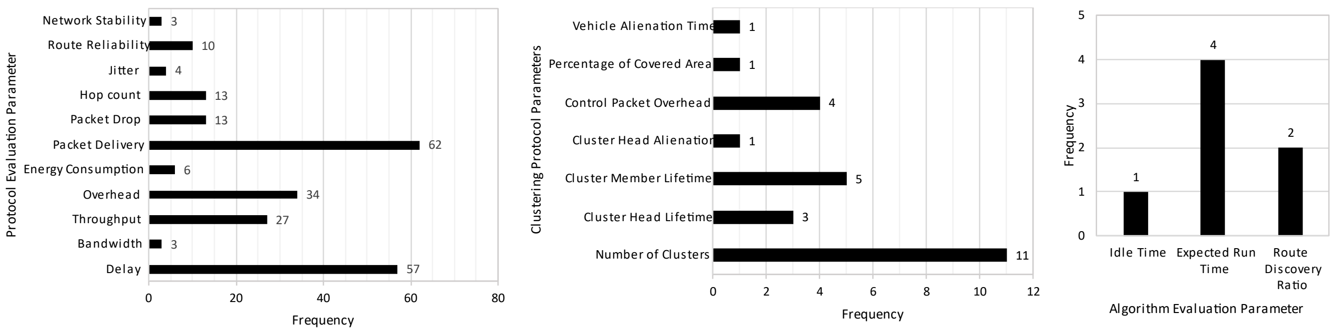
Fuzzy systems were used in 13 papers, and game theoretic approaches were adopted in only one paper.

Overall, the heuristic and SI techniques were implemented in 83.72% of articles, sometimes used in conjunction with other AI/ML approaches. ML techniques were used in 20.93%, fuzzy systems were found in 15.12%, and the game-theoretical approaches corresponds to 1.16% of included articles.

Figure 2(A) corresponds to the general measurements used for evaluating the performance of routing protocols. The prevalent parameters are packet delivery and end-to-end transmission delay, used in 62 and 57 papers, respectively. Routing overhead and throughput are mentioned in 34 and 27 papers, being also accepted as important and relevant metrics in the context of intelligent VANET routing. Other less popular metrics are not as consensual, with hop count and packet drop being employed in 13 papers.

This review has also found that clustering-based protocols, due to the uniqueness of the clustering concept, requires evaluation to consider certain specific parameters. As shown in Figure 2(B), the number of clusters is the most used parameter, with a frequency of 11 studies. Other parameters such as cluster member lifetime and control packet overhead were also considered in multiple papers (five and four, respectively).

Apart from protocol performance, algorithm efficiency was also evaluated on some studies (Figure 2(C)). The main considered metric was how long the algorithm took to converge to a good solution, described as expected run time.



(A) (B) (C)

Fig. 2. (A) General protocol evaluation parameters; (B) Clustering-based protocol evaluation specific parameters; (C) algorithm evaluation specific parameters.

IV. Discussion

A. *Activity in AI/ML-based VANET routing*

The results regarding the volume of work over the years have shown that, while before 2013 the papers applying AI/ML methods to VANET routing were scarce, following 2013 it has seen an increase in publications and of the interest of the scientific community.

Due to the snowballing procedure being undertaken between November 2020 and January/February 2021, articles published in late 2020 and early 2021 may have been overlooked, which leads to the decrease presented in Figure 1.

The increase in research in the field has been driven by the rise of the popularity of vehicular networks and communication, and the increase in the development of AI/ML algorithms. In the field of intelligent transportation systems and vehicular networks, the year of 2010 was marked by the launch of the IEEE 802.11p standard, which is one of the cornerstones for wireless access in vehicular environments, and, hence, a key technology for the future of VANETs [114]. The beginning of the last decade has also seen the expansion of AI/ML through the general improvement of its capabilities.

Apart from the gains in popularity of AI/ML and vehicular networks, one of the main contributors to the adoption of AI/ML algorithms in VANET routing is the wide acceptance of bio-inspired heuristics and fuzzy-logic systems as appropriate and effective techniques to improve quality of service (QoS) in ad hoc networks. While bio-inspired algorithms are not new to other fields of study, they have only began to be applied to solving routing issues in ad hoc networks at around 2009-2012 [115]. Thus, research motivation is multifactorial, being derived from the popularity of the field, the importance of improving network performance in VANETs and the advances in the fields of bio-inspired algorithms and heuristics.

B. *AI-based protocols taxonomy*

This study has found that intelligent VANET routing protocols can be grouped into six main categories, namely:

- Topology-based protocols: Messages are forwarded towards a single destination (unicast) based on topological information stored in the topology table of the router. Protocols can either be reactive (perform route discovery only when it has a message to forward) or proactive (constantly updates the topology table, even when not forwarding any messages).
- Geography/Position-based protocols: Messages are forwarded based on geographical information typically achieved through GPS data, as opposed to topological metrics.
- Clustering-based protocols: Nodes are grouped together, and one is selected as the cluster head (CH). The CH acts as a gateway, with communication between nodes in different clusters needing to be sent through the CHs.
- Multicast protocols: Destination consists of a set of nodes to which messages are to be sent, instead of a single node.
- Geocast protocols: Similar in nature to multicast, with the difference being that the destination correlates to a geographical area. E.g., in the case of a car accident, messages are sent to every node in the geographical zone preceding the accident, as to warn drivers to be careful and to reduce the speed of the vehicle.
- Hybrid protocols: Protocols which combine features of different other classes, such as the HyBR protocol [99], which is a combination of geography-based and topology-based routing.

The results have shown that the topology-based protocols are the most dominant, followed by the geography and the clustering-based protocols. Topology-based protocols are sound candidates for improvement using AI/ML techniques. In particular, the AODV (Ad hoc On-demand Distance Vector) [116] and the OLSR (Optimized Link-State Routing) [117] protocols were used in several studies as the basis for intelligent protocols and multiple approaches focused on optimizing the protocols' configurations based on a set of metrics, resulting in the improvement of overall performance and adaptability. Regarding the geography-based protocols, the GPSR (Greedy Perimeter Stateless Routing) protocol [118] has been a staple in the research found, with several articles either referring to comparisons with GPSR or presenting protocols based on GPSR. In both geography and topology-based protocols, AI/ML techniques were used in route discovery, successfully establishing the best route considering a set of criteria. Thus, the simple concepts and the intuitive implementation of topology and geography-based protocols, bolstered by the maturity and popularity of the AODV, OLSR and GPSR protocols, are key factors that influence studies to be focused on these two types of protocols.

Clustering-based protocols are based on both topology and geography-based protocols, and, thus, have many advantages and disadvantages in common. It is the third most frequent protocol type found in the reviewed works, and research is trending towards an increase in the acceptance of such protocols, as demonstrated by Figure 6, where between 2018 and 2020, it has been the dominant protocol type. Con-

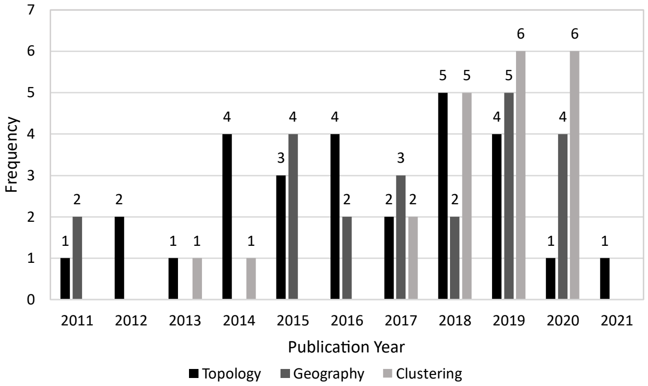


Fig. 3. Topology, geography, and clustering-based protocols' articles, by publication year.

sequently, it is undeniable that clustering is a principal concept in the development of future VANET routing protocols. In such techniques, AI/ML techniques were mostly used in cluster formation (evaluating the nodes based on their movement patterns), CH selection and cluster management, attempting to minimize the number of clusters needed, while choosing the most capable nodes as the CHs and minimizing the instability caused by vehicles that move between clusters.

The multicast and geocast protocol types represent a smaller number of papers. This is mainly due the nature of these protocols, as they focus on warning message dissemination, such as in emergency scenarios, while the previous protocols considered a wider range of applications. In multicast, the aim of AI/ML is to find the optimal multicast tree from source to destination based on defined criteria, such as delay, distance, jitter and bandwidth, which are considered in [109]. In geocast protocols, the concern lies in next-hop vehicle (NHV) selection, in which AI/ML techniques are used to select the most reliable NHV based on, e.g., position, speed and direction.

C. *AI techniques and methods*

Multiple AI/ML techniques have been used to improve performance in VANET routing, as demonstrated by the results presented in Table III. This study's findings show that heuristics and SI are promising approaches to route discovery.

The problem of choosing the best route while ensuring the highest level of QoS across multiple parameters is a key issue in the future of VANETs, and is considered as a NP-Hard problem [119]. Research has shown that heuristics and SI approaches can achieve good results in solving complex problems in dynamic environments, including NP-Hard problems. These methods have also been successfully used in the routing of vehicles, presenting interesting prospects as to the future of intelligent transportation [21]. These findings are evidence to the effectiveness of such techniques and justify their popularity in routing applications in VANETs.

In contrast, ML algorithms are used in a small number of studies. This can be attributed to the challenge in applying supervised and unsupervised learning algorithms to problems in such highly dynamic environments and to the wide acceptance of bio-inspired algorithms and heuristic approaches. Despite the unfavourability of supervised and unsupervised learning, the reinforcement learning (RL) approaches have been regarded with some interest. While the supervised and unsupervised learning methods were typically combined with heuristics, RL methods consist of either stand-alone solutions, or solutions augmented by fuzzy systems. The effectiveness of RL to solve routing problems has been demonstrated in a number of studies covering routing in traditional networks, wireless sensor networks, and in software-defined networks [120]–[123]. Hence, RL is regarded as one of the strongest approaches, especially when combined with fuzzy systems.

Fuzzy-logic systems are used to represent vagueness and imprecision, and fundamental in supporting decision making in changing environments, such as in the field of robot navigation and routing [124], [125]. Its usefulness in dynamic environments comes from the fact that these environments are characterized by impressiveness and unpredictability, which can be modelled under fuzzy logic, in turn enabling decision making to occur based on the environment's partial and imprecise information. The applicability of fuzzy logic to physical node routing and mobility upholds the effectiveness of fuzzy logic methods in data routing in VANETs.

It is to be expected that research trends in VANET routing will continue to focus on fuzzy logic, alongside heuristics and RL models, to improve the intelligence of routing protocols, and to provide a strong base for ad hoc applications.

D. *Performance evaluation*

Many parameters were used in the evaluation and comparison of intelligent routing protocols in the reviewed articles, however, there seems to be a consensus on the adoption of end-to-end transmission delay and packet delivery ratio (PDR) as the two main parameters to consider. Routing overhead (resulting from control packets) and overall data throughput are also important concerns in multiple papers. These four metrics are regarded as the primary QoS parameters in V2V communication. A case can be made for the assumption that the remaining parameters are based upon the four previous metrics, attempting to simplify their calculation. For example, packet drop is directly related to packet delivery, and route reliability and hop count are local metrics that attempt to model delay, throughput and overhead. An exception to this hypothesis is the energy consumption metric, which corresponds to the energy used in wireless communications. Although energy consumption is an important metric in MANETs, in vehicular nodes with virtually unlimited power supply for communication, energy is not an issue [126].

Findings have also illustrated that, while both delay and PDR are key concerns in intelligent VANET routing protocol design, certain protocol types require specific metrics to be analyzed, such as clustering-based protocols, which are often evaluated based on the number of clusters (since a lower value indicates higher network stability), and cluster member and CH lifetimes (directly related to network stability).

Aside from network performance, algorithm evaluation has also been conducted, in terms of the time taken to converge onto a solution and its quality, given a set of measurements such as hop count and delay. Although, the efficiency and effectiveness of algorithms is an interesting insight when designing a routing protocol, their usage in protocol evaluation and comparison is ill suited, as their relevancy derives from the correlation to QoS metrics such as delay and packet delivery.

E. *Main challenges*

As use cases for VANETs are beginning to come into fruition, driven by advances in intelligent vehicle technologies, research, and investment by car manufacturers, engineers are required to ascertain which routing protocols will be employed in such systems. The literature on the comparison of VANET protocols is lacking the use of a standard framework of evaluation and simulation, which are required to support the selection of adequate protocols. Hence, protocols need to be uniformly and rigorously compared using a standard set of performance metrics and simulation scenarios. Based on this review's findings, we recommend that the metrics used to devise the framework should be end-to-end delay, PDR, throughput, and routing overhead, with a special mention of number of clusters and cluster head and member lifetimes, in the case of clustering-based protocols. Moreover, the studies' results should be transparent and, preferably, open to access, contributing both to the reliability and to the respectability of the solutions.

V. Conclusion

Data routing in VANETs suffers from route instability and intermittent communication due to the high mobility of vehicles, characteristics that challenge the design of protocols as they attempt to push performance and QoS. This systematic literature review has focused on the development of intelligent routing protocols through AI/ML methods to improve network performance. Following the analysis of 86 articles, included based on a specific set of criteria and gathered through the snowballing process, results present promising prospects.

The results gathered prove that network performance (mainly measured in PDR, delay, throughput, and routing overhead) can be augmented by intelligent solutions, with special emphasis on heuristics, fuzzy systems and RL techniques, which have emerged as the most prominent and effective approaches to the routing problem in VANETs. AI/ML techniques are used to perform cluster formation and management, route discovery, shortest multicast tree calculation (solving the Steiner tree problem), among other applications that enhance network performance.

Papers proposing intelligent, effective, and efficient protocols has increased over the last decade. With so many prominent protocols being developed and published, and without a consensual adoption of a set of evaluation parameters, we suggest the development of an evaluation and comparison framework which encompasses the measurements to be considered, among other parameters. The definition of such framework provides the basis to better qualify each protocol's characteristics and in which VANET applications (e.g., warning message dissemination or infotainment) can then provide the best results. Transparency can play a key role in the accrediting and improvement of intelligent VANET routing protocols.

The inclusion criteria applied to the snowballing procedure led to the inclusion of a large set of papers, resulting in the authors' decision to not move onto a third and possibly fourth iteration. Despite this shortfall, the included works can be considered as representative of the domain of AI/ML-based VANET routing, since a large and heterogenous sample of works has been obtained. Nevertheless, in the future, the authors plan to revise the work with tighter inclusion criteria.

Acknowledgements

This work has been supported by FCT – Fundação para a Ciência e Tecnologia within the R&D Units Project Scope: UIDB/00319/2020.

Conflict of Interests

The authors hereby declare no conflict of interests.

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