

The evolution of routing in VANET: an analysis of solutions based on artificial intelligence and software-defined networks

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Article Info

Article history:

Received Nov 19, 2024

Revised Jul 18, 2025

Accepted Sep 14, 2025

Keywords:

Artificial intelligence

Machine learning

Routing

Software-defined networks

Vehicular ad hoc networks

ABSTRACT

This study explored the evolution of vehicular ad hoc networks (VANET) and focused on the challenges and opportunities for routing in these dynamic environments. Despite advancements in traditional protocols, a significant gap persists in the ability to adapt to highly mobile environments with variable traffic, which limits routing efficiency and quality of service. Emerging technologies, such as artificial intelligence (AI) and software-defined networks (SDN), are discussed that have the potential to revolutionize the management of VANET. Machine learning can be used to predict traffic, optimize routes, and adapt routing protocols in real-time. Furthermore, SDN can simplify routing management and enable greater flexibility in network configurations. A comprehensive overview of the convergence of AI and SDN is presented, and the potential complementarities between these technologies to address routing challenges in VANET are explored. Finally, the implications of efficient routing in VANET for road safety, traffic management, and the development of new applications are discussed, and future research lines are identified to address challenges such as scalability, data security, and computational efficiency in vehicular environments.

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1. INTRODUCTION

Vehicular ad hoc networks (VANET) have revolutionized the way we interact with vehicles, offering a wide range of services that improve transportation safety and efficiency. As an essential component of intelligent transportation systems (ITS), VANET play a key role in improving road safety. By enabling communication between vehicles, infrastructure, and other road users, VANET facilitate the development of collision warning systems, optimize traffic flow, and offer assistance to drivers. Therefore, they contribute to creating safer and more efficient driving environments [1]–[4]. However, efficiently routing data packets in such dynamic and highly mobile environments presents a significant challenge. Constantly changing topology, interference, and varying communication links complicate the design of robust and scalable routing protocols. This article employs a systematic review approach to explore the evolution of routing in VANET, with a focus on solutions based on artificial intelligence (AI) and software-defined networking (SDN). A structured search of scientific databases and a co-occurrence analysis of terms were conducted, allowing us to identify and synthesize the most relevant research in the field.

Artificial intelligence presents a novel approach to addressing these challenges. By applying machine learning (ML) techniques, such as reinforcement learning and neural networks, it is possible to develop routing algorithms that proactively adapt to changing network conditions and learn from past experiences. SDN provide a flexible and programmable platform for network management, allowing for the dynamic configuration of routing policies and improved integration with other VANET services.

This study focused on exploring how a combination of AI and SDN can revolutionize routing in VANET. The main challenges of routing in these environments are analyzed, the most relevant AI techniques are presented, and the proposed SDN architectures for VANET are discussed. Furthermore, the advantages and disadvantages of these solutions are evaluated, and future research areas are identified.

2. METHODOLOGY

This article was developed through a systematic review of the scientific literature to analyze the state of the art in VANET routing, with a particular focus on the integration of AI and SDN techniques. The steps in the methodological process followed to develop this review are described below.

2.1. Search strategy

The information collection was conducted through the indexed databases Clarivate Web of Science (WoS) and Scopus, which were selected for their broad coverage and relevance to the field of computational science and engineering. The search focused on articles published between January 2019 and July 2024, using combinations of key terms such as VANET, vehicular ad hoc networks, software-defined networking, machine learning, artificial intelligence and routing, the detailed search strategy for each database is presented in Table 1, while Figure 1 illustrates the methodology following the systematic review flow chart according to the PRISMA guidelines.

Table 1. Search strings used in the systematic literature review

Database	Equation
Scopus	TITLE-ABS-KEY ("Vanet*" OR "Vehicular ad hoc network*") AND TITLE-ABS-KEY ("machine* learning*" OR "ML" OR "SDN*" OR "software defined networking" OR "Software-Defined Networking")
WoS	TS=("Vanet*" OR "Vehicular ad hoc network*") AND TS=("machine* learning*" OR "ML" OR "SDN*" OR "software defined networking" OR "Software-Defined Networking")

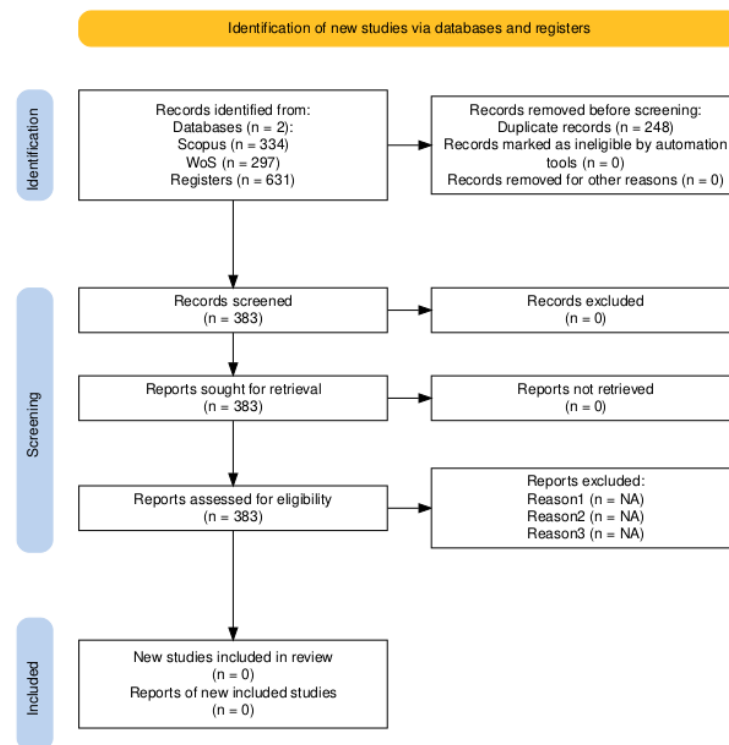


Figure 1. Methodology workflow for paper screening and inclusion according to PRISMA [5]

2.2. Inclusion and exclusion criteria

Review articles and original studies addressing routing solutions in VANET using AI, SDN, or other emerging technologies (such as UAVs, fog computing, 5G) were included. Only articles in English that were available in full text and with verifiable references were considered. Duplicate articles, conference publications, and papers whose primary focus did not fit the objectives of this review were excluded.

2.3. Preprocessing and cleaning the dataset

To ensure the quality of the analyzed set, a Python script called ScientoPy was used to clean the initial set of documents. This tool enabled us to identify and eliminate duplicate records between the two databases, while prioritizing the version indexed in the Web of Science. As a result of this process, a final set of 383 unique documents was obtained for analysis. From this refined dataset, 74 studies were ultimately selected through rigorous screening, focusing exclusively on AI, SDN, and emerging technology approaches to VANET routing, in strict adherence to methodological criteria.

2.4. Data analysis

The analysis was structured in two complementary phases:

- The VOSviewer tool was used to identify and visualize semantic relationships between key terms, generating co-occurrence maps that allowed us to identify trends, thematic clusters, and research gaps in the fields of VANET, AI, and SDN. Figure 2 shows the resulting co-occurrence map.
- Qualitative thematic analysis: The reviewed articles were classified according to the technologies used, algorithms applied, type of architecture proposed, advantages, limitations, and challenges identified. Comparative tables and supporting figures were also constructed to summarize the contributions of the analyzed articles, providing a structured view of the state of the art.

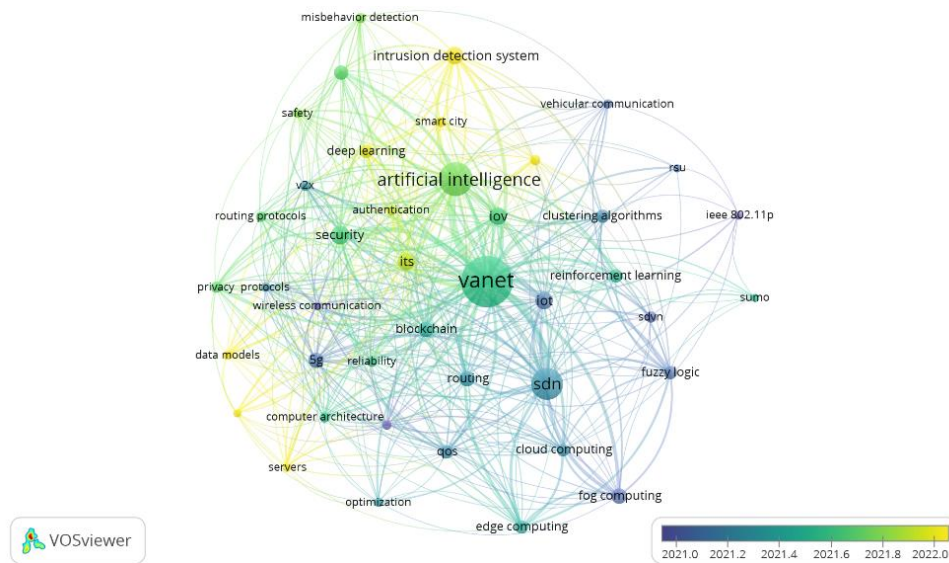


Figure 2. Map of key concepts and their relationships in the field of VANET, AI and SDN

3. REVIEW ARTICLES ON VANET

VANET have undergone significant evolution owing to the integration of technologies, such as ML and SDN. By centralizing network control and enabling programmability, SDN offers a solid foundation for efficient and flexible VANET management [6]–[9]. In contrast, ML can analyze large volumes of data in real time, allowing for optimized routing, congestion prediction, and improved security in VANET [1], [4], [10], [11]. ML has been proven to be a powerful tool for improving the efficiency and safety of VANET. Various ML techniques such as reinforcement learning and supervised learning have been explored to optimize routing decisions and predict relevant events [3], [12], [13]. For example, reinforcement learning enables vehicles to make optimal routing decisions in real-time by adapting to changing traffic conditions [12], [13]. However, the implementation of ML in VANET presents challenges such as the scarcity of labeled data and the need to develop computationally efficient models [13]. Furthermore, data privacy and security are key concerns, particularly in environments where sensitive information is shared between vehicles [14].

SDN offers a promising solution for optimizing VANET management. By separating the control plane from the data plane, SDN centralizes the control functions in a controller, facilitating the implementation of more efficient traffic management policies that are adaptable to changing VANET conditions [15], [16]. Network function virtualization, inherent to SDN, enables the integration of various communication technologies and optimizes resource management [17]. However, the implementation of SDN in VANET poses several challenges, including mobility management, security, and privacy. High vehicle mobility requires efficient handover algorithms to ensure continuous communication [16], [17]. Furthermore, the centralization of control in SDN introduces new security risks that must be mitigated by robust protection mechanisms [15], [17].

The integration of SDN and ML presents a unique opportunity to create a more innovative and resilient VANET. SDN provides a flexible infrastructure for deploying ML algorithms, whereas ML enables real-time network-decision optimization. However, this integration presents additional challenges, such as data quality and availability, as well as privacy and security concerns [1], [4], [10], [18]. It is necessary to develop ML models that are sufficiently lightweight to operate on resource-constrained devices that can adapt to dynamic environments. Advancements in technologies, such as 5G and cloud computing, along with the development of federated learning techniques [14], will address current challenges and unlock new opportunities for the application of ML in this field. Deep learning, as mentioned in [19], represents a crucial direction for addressing challenges such as network profile formation and coordination between control plane controllers. Table 2 compares previous review articles, including technical details, architecture, routing optimization metrics, proposals for future improvements, optimization criteria, and the technologies used.

Table 2. Comparison of routing review articles in VANET

Reference	Year	Protocols Details	Protocols Taxonomy	Discussion of SDN Architectures	Discussion of role of SDN in data Routing	Discussion of role of AI in data Routing	Data Routing Optimization Metrics	Protocols Application Area	Protocols Limitations	Protocols Robustness	Proposed Improvements	Comparison of Optimization Criteria	Analysis of performance evaluation	Simulation & Testbeds Tools	Future Challenges	New Trends and Upcoming Technologies	Technologies used	Main Topic
[1]	2022	✗	•	✓	✓	✓	•	✓	✓	✓	✗	✓	•	✗	✓	✓	Routing protocols	Routing
[3]	2020	•	•	✗	✗	✗	✗	✓	✓	•	✓	✗	•	✓	✓	✓	Vehicle communication technologies	Safety in autonomous vehicles
[4]	2020	•	✓	✓	✗	✓	✓	✓	✓	•	✓	✓	✓	✓	✓	✓	Artificial intelligence	Traffic management
[6]	2021	✗	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	Routing Protocols, AI	Routing protocols in IoV networks
[7]	2020	•	✓	✓	✓	✓	✓	✓	✓	✗	•	•	•	✗	✓	✓	SDVN	Routing schemes
[8]	2021	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	SDVN, routing protocols	Architecture and routing
[9]	2021	✗	•	✗	✗	✓	•	✓	✓	✓	✗	✓	•	•	✓	✓	Routing protocols	Routing in IoV
[10]	2020	•	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	AI, cognitive radio	Vehicle network management
[11]	2021	✗	•	✓	✓	✓	✓	✓	✓	•	✗	✗	•	✓	✓	✓	SDVN, vehicular cloud computing, vehicular fog computing	Architectures, taxonomy, benefits, use cases and challenges
[12]	2021	✗	✗	•	•	✓	✓	✓	✓	✗	✗	✓	✗	✗	✓	✓	Artificial intelligence	VANET challenges and requirements
[13]	2021	✗	✓	✓	✗	✓	✓	✓	✓	•	✗	✓	✓	✓	✓	✓	Cloud computing, edge computing, AI	VANET Challenges
[14]	2020	✓	•	✗	✗	✓	•	✓	✗	✓	✓	✗	✗	✗	✓	✓	IoT, AI, routing protocols	IoV architecture, routing protocols, problems, challenges and security
[15]	2018	•	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	•	•	✓	✓	SDN	IoV routing protocols
[16]	2020	✗	✓	✓	✓	•	•	✓	✓	✗	✗	✓	•	•	✓	✓	5G, SDN, fog computing	Mobility management
[17]	2021	✗	✗	✓	✓	✗	✓	✓	•	✗	✗	✗	✗	✗	✓	✓	SDN, 5G	Architecture for 5G
[18]	2019	✗	•	✗	✗	✗	✗	✓	•	✗	✗	✗	✗	✗	✓	✓	Artificial intelligence	Contextual awareness in advanced vehicle systems
[19]	2019	✗	•	✓	✗	✓	•	✓	✓	✗	✗	•	✗	✗	✓	✓	Artificial intelligence	Challenges and opportunities of ML and deep learning techniques in wireless networks

Note: The symbol ✓ indicates that the category was used, the symbol • indicates that the category was partially used, and the symbol ✗ indicates that the category was not used

The integration of SDN and AI is presented as a solution with significant potential for optimizing routing in VANET. AI, with ML techniques such as reinforcement learning, allows vehicles to make optimal routing decisions in real time, adapting to changing traffic conditions [3], [12], [13]. However, SDN facilitates the implementation of more efficient traffic management policies owing to the centralization of

control functions in controllers [13]–[17]. The combination of both technologies can lead to the creation of more innovative and more resilient VANET with optimized routing that dynamically responds to network conditions [15]–[17]. However, it is crucial to address challenges related to the scarcity of labeled data, need for computationally efficient models for ML implementation, and data security and privacy, especially when sharing sensitive information between vehicles [1], [4], [10], [13]–[18].

4. VANET AND ARTIFICIAL INTELLIGENCE

The application of AI to VANET routing protocols is transforming the development of intelligent, efficient, and safe transportation systems. Owing to the dynamic nature and high mobility of the nodes in VANET, traditional routing faces significant challenges. AI, utilizing techniques such as machine and deep learning, offers innovative solutions to these problems. For example, supervised machine learning using decision trees and neural networks has been used to predict link quality and packet delivery probabilities [20]–[23]. Unsupervised learning, with clustering algorithms, groups vehicles to select the best nodes in traffic management [24], [25]. Reinforcement learning, such as the Q-learning algorithm, allows vehicles to learn from their experiences and dynamically adapt routes based on feedback from the environment [23], [26]–[30]. Furthermore, deep learning, specifically using deep long short-term memory recurrent neural networks, has been applied to predict the travel time of emergency vehicles and optimize their routes and response times [31].

A prominent use case is vehicle trajectory prediction, which optimizes safety message dissemination [32] and facilitates intelligent next-hop selection based on traffic density and route lifetime [22], [27], [29], [33]. AI has also been employed to mitigate broadcast storms in NDN-VANET by using Bayesian classifiers for forwarding decisions [23]. Other methods, such as particle swarm optimization (PSO) coupled with the density peak clustering (DPC) algorithm, are employed to select the best vehicles as cluster leaders, thereby enhancing routing stability and performance [34]. These use cases demonstrate the potential of AI to optimize traffic management, improve road safety, and facilitate vehicle-to-vehicle communication. AI can predict vehicle movement [34], [35], optimize routes by considering traffic density and link quality [35], [36], and mitigate congestion through alternative routes [31], [33]–[36].

The integration of AI into VANET has significant potential for improving routing efficiency, reducing congestion, increasing packet delivery rates, and minimizing data transmission delays [26]–[30], [32]. At the security level, AI contributes to detecting and preventing attacks, authenticating nodes, and protecting user privacy [23], [37]–[39]. However, implementing AI in VANET poses challenges, such as intermittent connectivity, resource limitations, and data privacy protection [20], [24], [27], [28], [30], [32], [38]–[42]. Future research should focus towards developing more efficient AI algorithms, improving real-time data collection, and integrating AI with technologies such as blockchain and edge computing [21], [22], [26]–[28], [37], [39]–[41]. This convergence promises to revolutionize mobility, creating safer, smarter, and more connected transportation systems. Figure 3, which illustrates the distribution of these algorithms by category, provides a clear view of the impact of AI in this field.

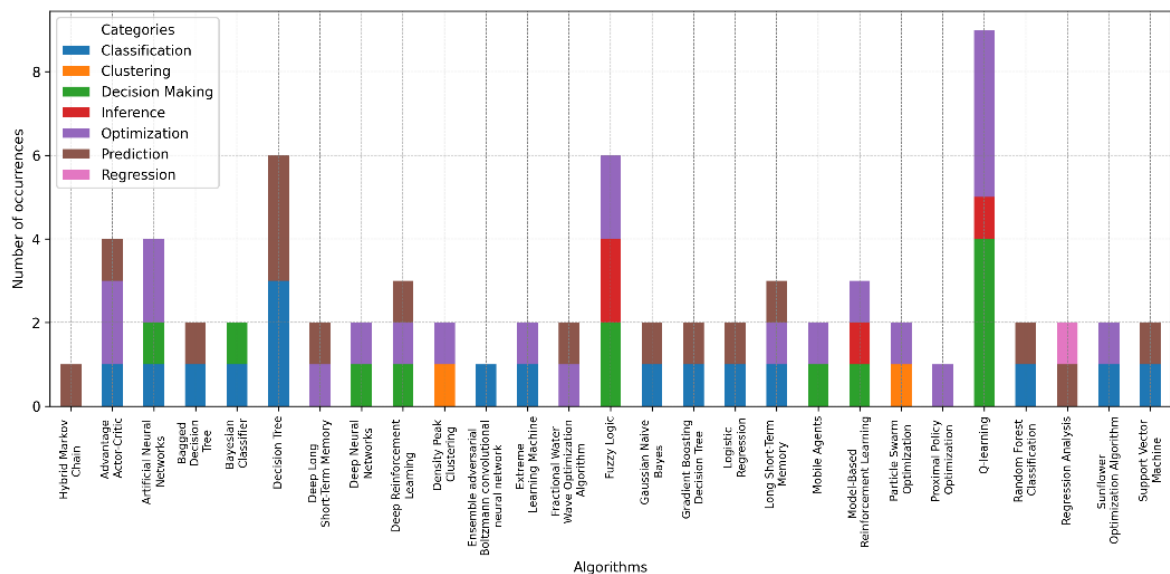


Figure 3. Distribution of AI algorithms used in VANET by category

5. VANET AND SOFTWARE-DEFINED NETWORKS

Integrating software-defined network (SDN) into VANET has emerged as a promising strategy for improving the flexibility and programmability of routing protocols in vehicular environments. SDN introduces a centralized controller that provides a global view of the network, allowing for more informed and efficient routing decisions compared to traditional protocols. This centralization facilitates dynamic adaptation to varying conditions, such as traffic density, vehicle mobility, and link availability, thus optimizing network performance in VANET [43]–[49].

Several use cases have highlighted the role of SDN in optimizing traffic and managing resources in VANET. For example, SDN enables traffic to be redirected towards less congested routes, thereby minimizing delays and improving the efficiency of vehicular flow [47]–[49]. In environments with high vehicle density, the SDN controller dynamically allocates resources such as bandwidth and processing capacity to vehicles and road units to improve the quality of service (QoS) [48], [50]–[54]. These SDN capabilities enable dynamic network reconfiguration [47], [55]–[62]; QoS optimization for different types of traffic [47], [48], [63]–[69]; and the implementation of centralized security policies, strengthening anomaly detection and protection against malicious attacks [44], [62], [70], [71].

However, the implementation of SDN in VANET presents several challenges. The complexity of the implementation is considerable because it requires the integration of specialized hardware and software in vehicles and roadside units (RSUs) [49], [55], [60], [62], [69], [72]. Furthermore, the centralization of network management introduces a single point of failure, where the failure of the SDN controller can impact the entire network's operation [49], [52], [62], [64], [71], [73], [74]. Scalability is also a significant challenge because the controller's ability to manage the network efficiently may be limited by an increase in the number of vehicles and network dynamics [49], [51], [54], [62], [69], [75].

Despite these challenges, SDN integration in VANET has the potential to optimize network performance and enable advanced applications in autonomous driving, road safety, and intelligent traffic management. Future research will focus on solving scalability, security, and deployment complexity issues to maximize the benefits of SDN in vehicular environments [21], [22], [26], [27], [28], [37], [39]–[41]. Although SDN integration in VANET has excellent potential for optimizing the network performance, its implementation presents significant challenges. Table 3 in Appendix summarizes the current research on SDN in VANET, revealing the diversity of approaches and technologies used to improve aspects, such as quality of service, security, and routing.

6. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

The integration of AI and SDN in VANET offers excellent potential for routing, but presents challenges that must be addressed to realize its benefits fully. Addressing the current challenges and exploring new avenues of research are critical. Open issues and challenges are described:

- a. **Implementation complexity:** Integrating SDN into VANET is challenging due to technology and protocol heterogeneity, requiring significant investment in hardware adaptation, software development, and component coordination. Vehicle diversity, constant mobility, and the need to integrate 5G and IoT further increase this complexity. Adopting open standards, such as OpenFlow, and ensuring security by design are crucial for effective mitigation.
- b. **Scalability:** VANET scalability is critical due to the exponential growth of connected vehicles. An SDN controller must efficiently manage increasing connections and dynamic topology changes amidst high vehicle mobility, increased traffic, and limited device resources. Solutions such as content delivery networks (CDNs) and microservice architectures can enhance scalability, but require careful consideration of latency and data consistency.
- c. **Data scarcity:** Developing machine learning models for VANET is limited by the lack of high-quality, high-volume labeled data, making manual collection and labeling costly. Techniques such as active learning and federated learning can mitigate this by allowing training with less data and distributing the computational load, but associated privacy and security challenges must be addressed.
- d. **Computationally efficient models:** ML models in VANET must be computationally efficient for resource-constrained devices. Techniques such as quantization, pruning, federated learning, and specialized hardware (graphics processing units (GPUs) and tensor processing units (TPUs)) can reduce model size, complexity, and improve performance. Balancing accuracy and computational complexity are crucial for low latency and reduced power consumption.
- e. **Data security and privacy:** Security and privacy are key concerns in VANET, as cyberattacks can compromise data integrity, confidentiality, and user safety. Robust authentication, authorization, encryption, anonymization, and pseudonymization mechanisms are essential to protect sensitive information and maintain user privacy.

- f. Prediction accuracy: The prediction accuracy of VANET is influenced by high network dynamics, data uncertainty, and model complexity. Improving accuracy requires data fusion techniques, hybrid models, adaptive learning algorithms, and considering environmental conditions and vehicle interactions in predictions.
- g. Computational complexity of AI: The computational complexity of AI algorithms, compelling deep learning models, poses a significant challenge for resource-constrained VANET devices. Model optimization techniques (quantization, pruning), specialized hardware, and exploring efficient neural network architectures like CNNs and RNNs can address this.

7. DISCUSSION

VANET are crucial for ITS, improving transportation safety and efficiency. However, efficiently routing data packets in such dynamic and highly mobile environments is a significant challenge due to constant topological variations, interference, and unstable communication links. The convergence of AI and SDN is emerging as a promising solution to these complexities, offering transformative potential but also entailing practical limitations that require detailed analysis.

a. AI-SDN convergence: potential and practical limitations

The integration of AI and SDN has significantly driven the evolution of routing in VANET. AI, through techniques such as machine learning and deep learning, enables VANET to predict traffic, optimize routes, and adapt routing protocols in real-time, thereby transforming network management from a reactive to a proactive approach. SDN, for its part, offers a flexible and programmable platform that centralizes network control, providing a comprehensive view of the topology and facilitating the dynamic configuration of routing policies. The integration between the two technologies creates a robust architecture where AI provides intelligence for decision-making and SDN facilitates its implementation and control, optimizing routing and democratizing the management of complex networks.

b. Security and privacy in emerging solutions

Security and privacy are fundamental concerns in VANET, given the amount of sensitive information shared and their critical role in road safety. AI plays a crucial role in enhancing security by detecting and preventing attacks, authenticating nodes, and safeguarding privacy by identifying anomalous behavior. SDN complements this by centralizing security policies, enabling faster threat responses and effective mitigation. The combination of AI and SDN enables robust trust mechanisms, and emerging technologies, such as blockchain, are being explored to strengthen authentication and data integrity further, driving predictive and proactive security.

c. Integration with complementary technologies: 5G, Edge and UAVs

The future of VANET is closely tied to integration with complementary technologies that enhance its capabilities. 5G technology, with its ultra-fast speeds and low latency, is essential for demanding vehicular applications such as autonomous driving. Edge computing brings computing resources closer to vehicles and RSUs, reducing latency by processing data locally. Uncrewed aerial vehicles (UAVs) offer flexible, on-demand network coverage, acting as mobile relays. This integration, combined with SDN, enables dynamic resource allocation and optimized routing, fostering a distributed intelligence paradigm and improving network resilience.

8. CONCLUSION

The evolution of VANET has been explored with a particular focus on the challenges and opportunities presented by routing in these dynamic environments. A thorough analysis of the scientific literature revealed that integrating AI and SDN is a key strategy for overcoming the limitations of traditional routing protocols and enhancing the efficiency, security, and reliability of VANET. The ability of AI to analyze large volumes of data in real-time, coupled with the flexibility and centralized control offered by SDN, has given rise to innovative solutions that enable more intelligent and adaptive traffic management. This study aimed to systematize the existing knowledge on the joint use of AI and SDN in the context of VANET, providing an updated framework for the current solutions, their strengths, limitations, and potential areas for improvement. Machine learning, a branch of AI, has proven to be particularly useful for optimizing routing in VANET. Various techniques, such as reinforcement learning, supervised learning, and unsupervised learning, have been successfully applied to predict vehicle mobility, estimate link quality, and select optimal routes based on changing traffic conditions. SDN, on the other hand, provides the infrastructure required to implement these AI algorithms efficiently, centralizes network control, and allows the dynamic configuration of routing policies. Among the most significant findings, it was identified that the use of centralized SDN controllers, combined with deep or reinforcement learning techniques, has

demonstrated substantial improvements in key indicators, including packet delivery rate, average latency, and bandwidth efficiency. Furthermore, a growing trend toward the development of hybrid and distributed architectures was observed, which partially addresses the scalability problem.

Despite the transformative potential of AI and SDN, their implementation in VANET remains challenging. The complexity of integrating specialized hardware and software, SDN controller scalability in the face of an increasing number of vehicles, the scarcity of labeled data for AI model training, the computational efficiency of algorithms on resource-constrained devices, and the security and privacy of data shared between vehicles are some of the hurdles that need to be addressed. Future research in this field will focus on developing solutions that overcome these limitations, such as distributed control architectures for SDN, more efficient machine-learning techniques, and robust security and privacy mechanisms. Significant gaps in the literature were also identified, including limited validation in real-world environments and a lack of comparability between algorithms under standardized conditions. This highlights the need for collaborative efforts between academia and industry to evaluate proposals in testbeds or advanced simulators that reflect realistic urban scenarios. It is essential to note that the integration of AI and SDN in VANET extends beyond routing optimization. These technologies can also contribute to improving road safety by detecting traffic anomalies, preventing malicious attacks, and authenticating nodes. Research in this area is expanding to incorporate emerging technologies, such as edge computing and blockchain, to enhance further the efficiency, security, and reliability of VANET. The convergence of AI, SDN, and other innovative technologies will pave the way for a future in which VANET will play a pivotal role in creating more intelligent, safer, and more sustainable transportation systems. Continued research in this area promises to revolutionize mobility and transform the way we interact with our environments.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Octavio José Salcedo Parra		✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓
Jorge Gómez	✓		✓	✓		✓	✓	✓	✓	✓	✓	✓		✓

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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APPENDIX

Table 3. State of the art, architectures and technologies in VANET research with SDN. The symbols "C", "D", "H" and "-" indicate centralized, distributed, hybrid and determined respectively

Ref.	Aspect that improves	Main feature	Aspect to improve	SDN architecture type	Technologies used
[43]	Increases the speed and connection capacity in vehicular networks.	Integrating SDN and 5G in a hierarchical architecture	Greater efficiency in data transmission and network management	C	5G, fog computing, massive MIMO, D2D
[44]	Efficiency and reliability of communication in random routes.	Software-defined Traffic Management Routing Protocol (SDTMRP)	Performance in terms of delay, throughput ratio and packet delivery	C	Routing Protocols
[45]	Reduce lag in connected vehicle applications.	Introduction of a multi-level MEC structure and intelligent core network	Increased latency efficiency, reduced congestion and improved reliability	D	MEC, SDN, DSRC, C-V2X, IEEE 802.11p, IEEE 802.11bd, FiWi
[46]	Optimizes information transmission and traffic control.	Load-based traffic redirection using SDN and a proxy	Package delivery rate and round-trip time	C	OpenFlow
[47]	Optimizes data transmission and resource management in hybrid networks.	Development of a centralized TDCR mechanism to optimize data delivery	Quality of service and cost reduction	C	DSRC, C-V2X, clustering algorithms
[48]	Reduces delay in task processing in vehicular networks.	Mobility-aware task offloading scheme	Reducing task calculation delay	C	Markov predictor of order k, SDN
[49]	Safety and Efficiency of Vehicular Networks Combining SDN and NDN.	NSDIoV architecture integrating SDN and NDN to address routing and security issues	Security and efficiency in detecting and mitigating attacks	C	IEEE 802.11p
[50]	Reduces power consumption and improves failure recovery.	Location-aware routing algorithm to minimize energy consumption	Reduced energy consumption and enhanced failure recovery	C	Fog computing, 5G
[51]	Optimizes the dissemination of safety information and reduces delay.	Multipath routing with minimal latency	Significant reduction in delay, increase in delivery rate and decrease in overhead	H	Fog computing
[52]	Optimizes resource allocation in vehicular networks.	Integrating EC and SDN to optimize resource allocation in VANET	Improved QoS, reduced delay and decreased overhead	H	Multi-agent reinforcement learning (RL), deep Q-learning algorithm
[53]	Optimize edge cloud resource management for vehicular networks.	Integrating SDN into the RSU cloud to dynamically manage resources	Minimizing latency and improving overall network efficiency	D	OpenFlow, IEEE 802.11p
[54]	Data transmission between vehicles.	Using SDN and fog computing to calculate the best route	Network performance	H	Fog computing, OpenFlow, GPS, IEEE 802.11
[55]	Stability of links for data transmission.	SDN-based routing scheme using multi-layer information	Reducing packet loss and delay	H	OpenFlow, LTE-A, DSRC, WAVE, GPS
[56]	Optimizes data transmission by considering different factors.	Optimized routing and scheduling scheme for multi-hop scenarios	Higher packet delivery rate and lower delay, especially for real-time traffic	H	DSRC, IEEE 802.11p, optimization algorithms
[57]	Speeds up data transfer, especially for delay-sensitive applications.	Two different SDN architectures to manage transfers in VANET	Lower transfer times and greater robustness	C	OpenFlow, Ryu, IEEE 802.11/ WiFi, IEEE 802.11p/WAVE
[58]	Deliver data and reduce delay in multi-hop networks.	Optimized routing algorithm for multiple stable paths	Balancing packet delivery rate and latency	D	LTE, DSRC, optimization algorithms, shortest path algorithms
[59]	Optimizes vehicle traffic to improve network performance.	Modified traffic orchestration method in SDVN using multipath routing	Reducing complexity and optimizing channel loading	C	Modified reverse wave algorithm

Table 3. State of the art, architectures and technologies in VANET research with SDN. The symbols “C”, “D”, “H” and “-” indicate centralized, distributed, hybrid and determined respectively (*Continue*)

Ref.	Aspect that improves	Main feature	Aspect to improve	SDN architecture type	Technologies used
[60]	Increases the overall performance of the vehicular network.	Game theory-based centralized network selection mechanism	Overall network performance, lower latency and higher delivery rate	H	cellular networks, Wi-Fi, WiMAX
[61]	Routing efficiency and security in complex scenarios.	Integrating SDN and blockchain into routing protocols	Performance in packet delivery rate, latency and security	H	Blockchain, WAVE, LoRaWAN, LTE
[62]	Enhances network security by mitigating various types of attacks.	Open-flow SDN architecture based on encrypted blockchain	High efficiency in attack detection and improvement of QoS parameters	-	AODV, blockchain, OpenFlow
[63]	Availability in weak signal conditions.	Multi-hop cooperative data dissemination technique	Minimizing latency and maximizing network utility	D	Mobile Edge Computing (MEC), MHCDD protocols
[64]	Improves dynamic interface management and routing.	Practical framework for implementing SDN-based vehicular networks	Efficient BSM message routing merging	C	DSRC, 5G, Bluetooth, OpenFlow
[65]	Increases package delivery rate.	Using an ant colony algorithm to calculate the optimal route	Higher package delivery rate	C	Ant colony algorithm, Dijkstra's algorithm
[66]	Optimizes overall network performance, including power consumption.	SDN and fog integration computing to control transmission rate and optimize routing	Precise control of packet dissemination rate and improvement of overall performance	D	Fog computing, IoT,
[67]	Quality of service in aerial sensor networks.	Traffic Differentiation Routing Algorithm for FASNETs	Reduced latency for sensitive applications and improved data integrity	H	Ant colony algorithm, GPS
[68]	Increases the reliability and security of data transmission.	Combining SDN, Network Coding and MGM for data dissemination	Greater security and reliability in data transmission	C	Network coding, Multigeneration mixing (MGM), DSRC, asymmetric encryption
[69]	Increases package delivery rate and reduces delay.	Combination of Fog Computing, SDN and clustering for routing	Performance, low latency and high packet delivery rate	H	Fog computing, clustering, AODV, OpenFlow, GPS
[70]	Increases the reliability of data routing.	Delay-sensitive multipath routing integrating SDN	Greater efficiency in packet delivery, lower delay and better performance	H	IEEE 802.11p, LTE, Wi-Max
[71]	Stability and quality of data transmission service.	Routing framework for general vehicular networks	Optimizing latency without compromising link stability	H	DSRC, LTE
[72]	Reliability and efficiency in the dissemination of information in real time.	SDN architecture and HRPS algorithm for reliable route selection	High packet delivery rate and low delay under adverse conditions	C	DSRC, OpenFlow,
[73]	Optimizes network performance during data transfer.	Using SDN and MEC for a seamless handover scheme	Increased network throughput during transfer and reduced packet loss	H	MEC, IEEE 802.11p, LTE/5G
[74]	Reduce data delivery delays for vehicle-to-everything services.	eNBs and RSUs placement	Reducing latency requirements in V2X applications	H	MEC, eNB-type RSUs, IEEE 802.11p, OpenFlow, fuzzy logic clustering
[75]	Reduces power consumption and improves routing efficiency.	Introduction of SDN- FoG and DUEvR protocol to improve efficiency and routing	Reliability of data transmission and reduction of energy consumption	H	Fog computing, GPS, geographic information system (GIS), geographic routing protocol, IEEE 802.11p

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