

Secure Communication Protocols for Software-Defined Vehicles: A Machine Learning Approach

Venkata Lakshmi Namburi

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Abstract: Software-defined networking, sometimes known as SDN for short, is an intriguing method of networking that combines centralized management with network programming. When software-defined networking (SDN) is utilized, the control plane and the data plane are separated, and the network management is transferred to a central place known as the controller. In addition to being able to be programmed, this controller acts as the brain of the network. Over the past few years, the research community has shown a rising tendency to reap the benefits of current discoveries in artificial intelligence (AI) to increase their capacity for learning and decision-making in software-defined networking (SDN). It has been established that they have this propensity to boost their capacity to learn and to make judgments. This paper comprehensively overviews recent initiatives undertaken to incorporate AI into SDN. According to our research findings, the most often discussed topics in artificial intelligence were machine learning, meta-heuristics, and fuzzy inference systems. This study aims to evaluate the potential advantages of introducing AI-based approaches into the SDN paradigm and the possible uses and applications for these methodologies.

Keywords: Autonomous vehicle, Software-defined vehicle, Machine Learning.

Introduction

Information regarding automobiles is disseminated through a vehicular communication system to prevent traffic chaos, congestion, and accidents from occurring. Congestion, on the other hand, is a more major concern. Internet technologies necessitate an unparalleled network capacity and a high level of service (QoS) for automotive applications. When it comes to automotive applications, there are issues with lack of flexibility and inadequate task-offloading methods [1]. The Base Station (BS) and the Road-Side Units (RSUs) work together to adapt to network conditions and solve difficulties, such as task offloading. Quality of service in VANETs is improved as a result [2]. As a result of the high

mobility that exists inside a VANET system, link connection is subject to frequent changes dependent on the distances between vehicles (V2V) and infrastructure (V2I) [3]. The data packet is transmitted via cars through internet services represented by a queueing network [4]. The combination of heterogeneous vehicular networks with software-defined networking (SDN) has the potential to improve VANET network performance [6,7] and reduce traffic congestion [5]. Vanet and SDN connections aim to separate the data plane and the control plane [8]. As seen in Figure 1, software-defined networking (SDN) has received considerable attention in the last several decades. SDN aims to centralize network services, control, and flexibility in the wireless and ad hoc domains.

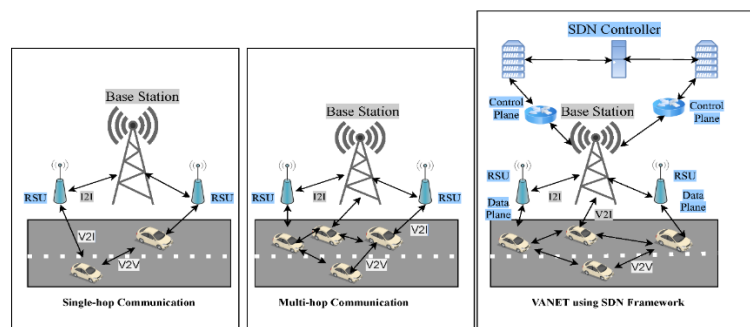


Figure 1. The SDVN architecture.

Research Scholar, B.E.S.T Innovation University
(BESTIU), Software Systems Engineer, Danlaw Inc.
Michigan USA. venkatanamburi91@gmail.com

In this survey, we explain how software-defined networking (SDN) technologies have the potential to be a promising solution to the issues that are present in-vehicle networks. These technologies also provide low-latency access to high-bandwidth applications and emergency services. Protocols, processes, and systems for managing handoffs are the primary focus areas in mobility management, a crucial component of vehicular networks [9]. As time goes on, mobility management becomes more and more critical. Mobility management in SDN-enabled vehicle networks is thoroughly covered in the survey, along with its models, difficulties, and potential solutions. The various mobility management solutions can be classified according to the vehicle network model utilized. Some examples include hybrid, SDN, HetNet, and fog-based technologies [10]. The survey's findings regarding the probable results and future paths of wireless networks can be helpful for young researchers working on intelligent VANETs. The research also delves into enhancing VANET traffic forecast by incorporating a stochastic vehicular mobility model that accounts for variations in inter-vehicle communication over time [11,12]. This model is used to help enhance traffic prediction.

Virtual Area Networks (VANETs) are transportation-related networks connecting mobility vehicles electronically. It is challenging to convey information via VANETs because of the prevalence of failures in these networks. VANETs face a significant obstacle in the form of modifications to their topology, which are brought about by high mobility and isolated nodes. The software-defined networking (SDN) paradigm is the one that VANETs use. This paves the way for VANETs to triumph over the challenges that SDVNs encountered earlier. It enhances the vehicular network's programmability and flexibility by analyzing data and making decisions about the network [13].

It is composed of a control plane that is logically centralized and analyzes the data.

Conventional networking has relied on infrastructure, with numerous routers dispersed to provide the control plane. With software-defined networking (SDN), the core network management mechanism is theoretically separated from routers and switches, allowing centralized network control [14].

The controller may build secure channels that meet the network's needs by going beyond what is achievable with conventional hardware-driven networking. Software-defined networking (SDN) makes the controller's ability to gather data regarding the network's present state feasible. SDN consists of the infrastructure, control, and application planes.

SDVNs offer several benefits that conventional networks do not, the most notable being flexibility and programmability. Through software-defined networking (SDN), physical devices can connect using a single protocol. This enables control to be centralized. With software-defined networking (SDN), we have been able to automate and virtualize networks, optimize traffic, and coordinate cloud-based services, among other things. A significant issue with software-defined networking (SDN) is that it needs to be more reliable. This is because the SDN controller often becomes a failure point. Also, conventional networks can't use OpenFlow. Therefore, software-defined networking (SDN) needs help integrating with them. Also, there are few protocols for the controller to communicate with applications, and the central controller can only handle some traffic on its own [13].

One variant of wireless networks is the software-defined virtual network (SDVN), which is short for software-defined wireless network (SDWN). By combining VANETs with software-defined networking (SDN), the SDVN architecture increases the flexibility and scalability of vehicular networks [11]. Regarding SDN controllers, their network awareness provides numerous benefits, such as adaptive node transmission power reservation, improved routing, and flexible radio interface placement. In addition to facilitating global optimization in VANETs, the SDVN allows enhanced networking functions, including routing and load balancing. Gathering data from networks makes this feasible. Another way it promotes innovation in networks is by making it easier and cheaper to test and deploy VANET technologies. Since the network's topology is constantly changing and the nodes are always moving around, the SDVN faces many difficulties. Difficulties arise due to insufficient security measures and complex network operations, including transmission and routing control [13].

Survey method

To perform benchmarking research on SDVNs, one must be well-versed in the criteria and utilize appropriate surveys. For this sort of research, some possible inclusion and exclusion criteria are as follows:

Inclusion Criteria

Inclusion requirements were as follows, as described below:

- There must be a connection between the surveys and SDVNs and network performance benchmarking.
- Surveys must have been published in academic publications that have been subjected to peer review or in conference proceedings.
- To ensure the research is current, surveys must have been published within a specific time frame, such as the past five years.
- Survey data collection and analysis processes must have used empirical research methodologies such as experiments, simulations, and case studies.

Exclusion Criteria

The following were excluded from this survey:

- Surveys that don't concern SDVNs or network efficiency measurement in any way.

- Surveys are only considered published if included in conference proceedings or peer-reviewed academic journals.
- Surveys are released after the specified deadline has passed.
- For example, surveys that failed to employ any empirical research approach.

The many subject areas and articles covered by scientific databases are separated into distinct categories. We chose databases that cover much ground based on the research question or topic. You can arrange them in a hierarchy based on the fields they support or the database data types they hold. A comprehensive literature search was conducted to find surveys that met these requirements. The research objectives and subject matter dictated the databases used, which included PubMed, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect, Scopus, Google Scholar, and others. Exact parameters and phrases were used to search. Searching reference lists and maintaining an eye on citations can help you uncover more relevant surveys, among other things. After a list of possible surveys has been generated, a screening method can be applied to determine which surveys satisfy the inclusion and exclusion criteria. Under these conditions, it is possible to capture the total amount of data shown in Figure 2.

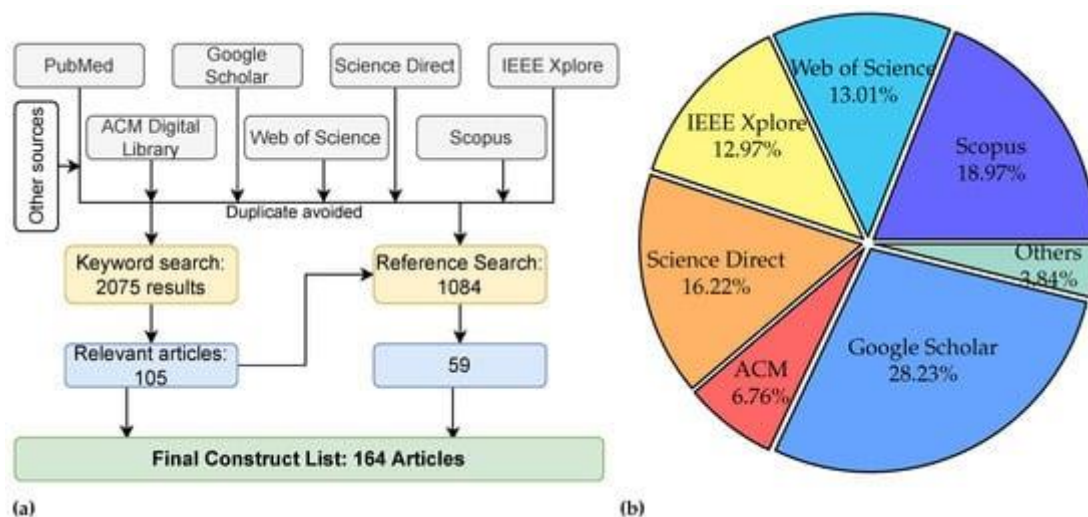


Figure 2. The entire procedure of acquiring samples for a database. (a) After removing duplicates, assess the building to add and remove papers. (b) The proportion of articles that were screened across multiple scientific databases before duplicates were removed.

The importance of software-defined networking (SDN) as a component of next-generation networking technologies has grown in recent years. 5G, the Internet of Things, fog/edge computing, wireless/mobile networks, network functions

virtualization, sensor networks, VANET, and many more are all part of this group of technologies [14,15].

We will summarize the most significant contributions of this study in relation to previous surveys as follows: 1. This overview delves into the latest advancements in software-defined vehicular networks, covering topics such as architectures, key techniques, and solutions. 2. We look at the present-day consequences, the potential future study prospects, and the simulation tools that could be used in future studies. To evaluate our findings in relation to those of other researchers, we take a multi-dimensional look at VANETs, IDT, and the SDN controller placement problem (CPP).

Our assessments of each survey consider various views, such as modelling choices, aims, procedures, and evaluation criteria. Furthermore, we discuss novel networking paradigms that may use software-defined networking (SDN). As seen in Table 1, this survey covers a lot of ground and will guide future studies in certain directions. The DVD taxonomy is shown in Figure 4, while our survey's concentration is summarized in Figure 3.

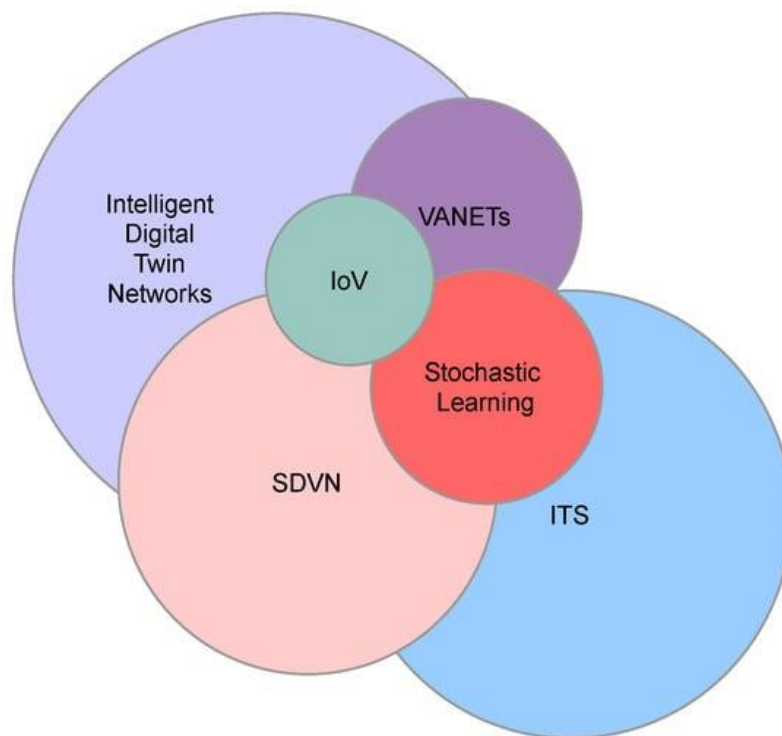


Figure 3. Future study paths and the depth of our survey.

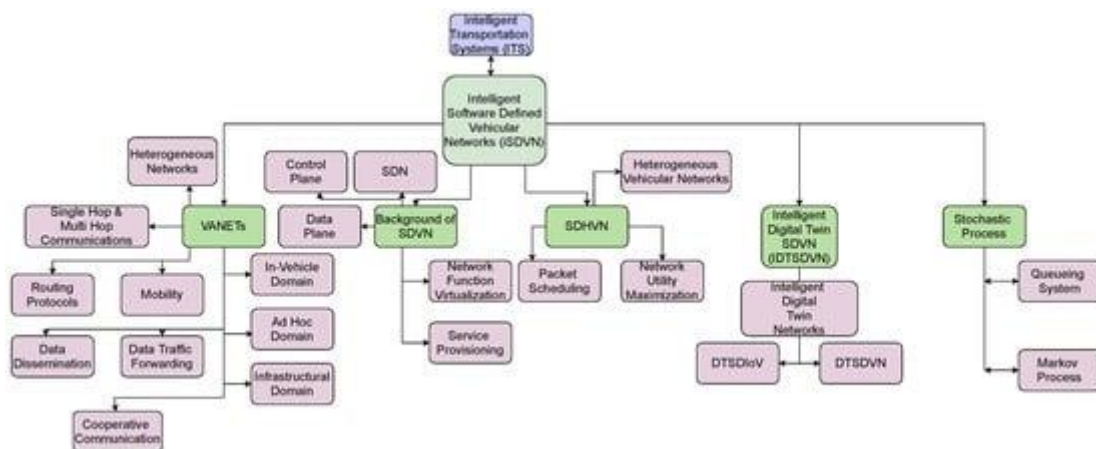


Figure 4. Classification of this iSDVN's structure.

Background: ISDVN System

Network topologies that are "intelligent SDVN" are defined by this phrase. The design is based on software management and configuration of the network's numerous hardware components, including switches, routers, and more. The concept behind SDVNs, or software-defined virtual private networks, is that they may be more easily adjusted and customized than traditional networks. This makes it easy to administer and modify the network if needed [17]. A central controller oversees the data plane and control plane of the network in the SDVN architecture. Through protocols like OpenFlow and application programming interfaces (APIs), the controller can create and control network traffic with various devices, including network switches. One significant advantage of software-defined virtual private networks (SDVNs) is that they allow network administrators to segregate the control and data planes, improving performance and reducing congestion [18]. A more automated and programmable network environment is another benefit of software-defined virtual private networks (SDVNs), which makes it easier to manage network resources and adjust to variations in traffic. Researching SDVNs from a performance testing perspective is essential due to these advantages. Researchers' attempts to compare the performance of various SDVN architectures to discover best practices and development possibilities ultimately lead to better and more efficient network designs [19].

Single-Hop and Multi-Hop Network Connectivity in SDVNs

A "single-hop connectivity" network configuration does not include intermediate nodes but directly connects the source and destination nodes. Figure 1 shows that the network topology eliminates intermediary nodes, allowing packets to travel directly to their destination node with minimal latency. Minimal latency is guaranteed by the direct connection between cars in a VANET [20]. This is the main benefit of VANETs with single-hop connectivity. Conversely, compared to other forms of connectivity, the transmission range of single-hop connectivity is significantly lower. When there is a large distance between the source and destination nodes, data flow must be routed through several intermediate nodes before it reaches its final destination. This is because single-hop networks have a limited transmission range. Figure 1 shows

how intelligent message broadcasting can alleviate channel load in a multi-hop network.

Furthermore, multi-hop routing could considerably enhance wireless networks' capacity and throughput, increasing traffic congestion inside the network [21]. In VANETs, the majority of the information that is important to safety is broadcast to all of the nodes in the network. Researchers have addressed the congestion problem in VANETs by developing multi-hop routing protocols.

Mobility

In SDVNs, it is possible for moving vehicles to communicate with one another through self-organizing, distributed networks. Even automobiles travelling at high speeds can be connected to an SDVN. SDVNs are either ineffective or unsuitable because of the high-speed motion of vehicles. An increasingly dynamic environment for network topology is created when the driver changes their direction and speed [22]. Given these considerations, the network protocol must have a robust connection to vehicle movement. Data traffic in software-defined virtual networks (SDVNs) may affect mobility due to the dynamic topology change in these networks. The connection between wireless communications and mobility is bidirectional [23]. Researchers have put a lot of time and effort into including mobility modelling and communication protocols in-vehicle networks. Data traffic optimization and mobility management are two primary outcomes of most SDVN protocols.

Routing

The four distinct types of routing described below are unicast, multicast, broadcast, and geocast routing [24]. SDVN unicast routing, which allows data packets to be transmitted between source and destination nodes, is also known as one-to-one communication.

SDVNs use multicast routing, sometimes called grouping or one-to-many routing, to broadcast packets from a single source to a collection of nodes [25]. Multicasting is extensively utilized in defence and military applications. This type of routing involves sending data packets from one network node to multiple other nodes.

This style of routing is also known as broadcasting. It is often used during calamities to ensure people's safety. Geocast routing sends packets to a group of nodes inside a defined geographic area. Geocast

group members are identified based on their position within a defined geographic area, whereas multicast group membership can occur anywhere inside an ad hoc network [26].

The following is a list of the various routing protocols that researchers have created to lessen the amount of latency that exists between the nodes that make up an SDVN:

Position-based routing protocol—The packet's routing from the source node is determined by the destination's physical location and IP address, accessed via the Global Positioning System (GPS).

Topology-based routing protocol enables packets to be transmitted from one node to another using the available information about the network's connectivity. Proactive, reactive, and hybrid approaches are the three primary varieties of proactive routing systems.

(a) **Proactive routing:** The shortest-path method finds the route and adds it to the routing table for this specific protocol. During periodic updates, this table is shared with the neighbours.

(b) **Reactive routing:** Routing was purportedly initiated when a node realized it needed to communicate with another. We call this "on-demand routing." Reducing network traffic is an advantage of using this protocol.

(c) **Hybrid routing:** The protocol classifies networks as local or global and then uses proactive and reactive routing techniques to lower latency and routing overhead for both networks.

Broadcast-based routing protocol: Sending data packets to each node in a car network is known as broadcast routing.

Cluster-based routing protocol—Consideration of characteristics like velocity and direction causes clusters to form in a network. This is done for communication. Communication between clusters and inside clusters is one of the responsibilities of the cluster head. The cluster head establishes a virtual network architecture to facilitate scalability when intra-cluster communication is through a direct link.

Geocast-based routing protocol— To communicate with vehicles inside a particular area, called the zone of relevance, one uses a mobicast message.

Routing in a Multi-Access Environment with Learning Approaches

Routing is an essential component of software-defined networks (SDNs) and virtual private networks (VANETs) since it specifies the path that packets take from their origin to their final destination. VANETs can utilize a variety of wireless technologies in multi-access contexts. The following technologies are included in this category: DSRC, cellular networks, IEEE 802.11p, and wireless LANs [27]. Learning techniques are commonly used in SDN and VANET routing to improve efficiency and adaptation to changing situations and dynamic network settings. The following learning approaches are frequently utilized in the routing process of SDNs and VANETs:

Reinforcement Learning— Agents learn to make judgments through the process of reinforcement learning (RL), which involves interacting with their surroundings. In software-defined networks (SDN) and virtual area networks (VANETs), routing decisions can be adapted using RL based on the perceived performance of various routes over time. This allows the network to master the art of route prioritization according to metrics like throughput, latency, and dependability.

Deep Learning—Deep learning methods such as neural networks can identify patterns and correlations in SDN and VANET data that conventional routing algorithms overlook. In dynamic and complicated SDN and VANET environments, the trained models may be able to make better routing decisions.

Context-Aware Routing—The notion of context-aware routing refers to making judgments about routing based on various contextual parameters, including vehicle speed, traffic density, and the quality of any links. Machine learning algorithms can adjust routing metrics based on the current context, resulting in improved route selection.

Federated Learning—Privacy and security are two important aspects to consider while using SDN and VANETs. Vehicles can train a model through a federated learning system, eliminating the need to share raw data with a centralized organization [28]. This method can improve routing decisions while maintaining the confidentiality of individual vehicles.

Online Learning—Routing algorithms on SDN and VANETs must be very adaptive because of the networks' inherent dynamic character. Given the

potential for online learning techniques to be applied to VANETs—networks in which the network topology might undergo quick changes—they are valuable for constantly updating routing decisions.

Multi-access virtual private networks (VANETs) have the potential to dramatically increase routing efficiency, dependability, and adaptability by utilizing these learning methodologies. However, learning-based routing algorithms are associated with a variety of issues. These challenges include concerns regarding scalability, security, and computational overhead. In addition, validation and testing in the real world are essential for these systems to work reliably and effectively in changing vehicle scenarios.

Machine learning and security

As illustrated in [29], machine learning approaches have been applied to nearly every networking challenge; naturally, security is also not an exception. The majority of the machine learning-based methods make use of the KDD'99 cup dataset [30], which is known to possess key flaws as outlined in [31] or its improved version NSL-KDD [32], even though a few of the mentioned algorithms demonstrate outstanding performance. Some of the varied features included in these datasets, such as the number of root accesses, file creation operations, or shell prompts, are unavailable at the start of the OW or outside the network domain, making them inaccessible to an SDN controller or switch.

Very few suggestions rely entirely on network characteristics. According to [33], SDN properties such as packet count, total bytes count, packet rate, first packet length, and average packet length should be used for every flow. The aforementioned model is aimed at detecting malicious traffic. There has been no measurement of the time it takes to identify the attack. However, the classifier generally will only be able to spot malware after the start of the flow because some variables are known only at the end of the flow, such as the number of packets, average length, and flow duration.

Other systems, similar to the one described in [34], take advantage of the information contained in the packet header, although they are more focused on intrusion detection systems (IDS). These systems continuously sniff packets and look for an intrusion in the middle of the flow. It may take some time for them to process and notify the network administrator

because they do not have any restrictions on detecting latency.

In addition to its use in network security, machine learning techniques have been implemented for various reasons on uncrewed aerial vehicle (UAV) systems, as demonstrated in [35]. According to the authors, the described machine learning solutions can be categorized into four different components of UAV-based communication: the physical layer, location, resource management, and safety and security. In addition to detecting GPS spoofing, most security recommendations focus on the physical components of the transmission rather than the network layer. These include eavesdropping, jamming, and spoofing. Deep learning, support vector machines (SVM), and reinforcement learning are some of the machine learning techniques contained in the machine learning techniques. These techniques encompass all algorithms, including supervised, unsupervised, semi-supervised, and reinforcement learning. Neural networks go all the way up to random forests.

The article [36] illustrates how machine learning can be utilized to ensure the safety of a UAV network. To mitigate four different types of cyberattacks, the authors have divided them into two categories: integrity attacks, which include GPS spoofing and the broadcast of false information, and denial of service assaults, which include jamming, grey and black hole attacks. The ground station receives a report based on detection rules computed by each uncrewed aerial vehicle (UAV). Using their recorded behaviour, a support vector machine (SVM) algorithm classifies the nodes. On the other hand, the method does not offer any countermeasures and results in increased overhead because of the transmission of reports. The authors of [37] come to the conclusion that "the intersection of machine learning algorithms to mitigate networking attacks has seemed to provide the most promise." This is after they said that most solutions aim to detect large-scale distributed denial of service attacks.

Conclusions

Several facets of SDVNs have been illuminated by the survey on stochastic modelling in intelligent SDVNs, providing helpful insights into these issues. The findings highlight several aspects of VANET and SDVN performance analysis, scheduling, data distribution, resource allocation, and routing. This review focuses on VANETs and how factors like

high mobility and dynamic network structure affect their resource allocation and response time. Within the context of cooperative communication situations, it identifies the necessity of appropriate coordination and scheduling mechanisms to maximize the flow of data traffic and the provision of services. Network performance, connection, mobility, data forwarding, collision avoidance, and software-defined virtual networks (SDVNs) are highlighted when VANETs and SDVNs are compared. Within the context of SDN-oriented automotive networks, it offers a detailed review of the approaches and solutions that are currently in use. On the other hand, the survey acknowledges the current constraints and difficulties in deploying SDN in automotive networks. A barrier to adopting SDVN is the requirement for off-the-shelf SDN controllers and switches customized to operate in automotive contexts. The poll recommends conducting additional studies and launching innovative ideas to solve these problems and establish mature solutions and standards for SDVNs. This survey highlights the possible benefits of integrating software-defined networking with digital twin technologies for better network management. The digital twin's capacity to optimize resources, provide real-time insights, and use predictive analytics makes it feasible to increase the efficiency and robustness of the SDVN system.

References

- [1] Chen, G.; Zhou, Y.; Xu, X.; Zeng, Q.; Zhang, Y.D. A multi-aerial base station assisted joint computation offloading algorithm based on D3QN in edge VANETs. *Ad Hoc Netw.* **2023**, *142*, 103098. [[Google Scholar](#)]
- [2] Al-Badarnah, J.; Jararweh, Y.; Al-Ayyoub, M.; Fontes, R.; Al-Smadi, M.; Rothenberg, C. Cooperative mobile edge computing system for VANET-based software-defined content delivery. *Comput. Electr. Eng.* **2018**, *71*, 388–397. [[Google Scholar](#)]
- [3] Ravi, B.; Kumar, M.; Hu, Y.C.; Hassan, S.; Kumar, B. Stochastic modeling and performance analysis in balancing load and traffic for vehicular ad hoc networks: A review. *Int. J. Netw. Manag.* **2023**, e2224. [[Google Scholar](#)] [[CrossRef](#)]
- [4] Dai, X.; Xiao, Z.; Jiang, H.; Chen, H.; Min, G.; Dustdar, S.; Cao, J. A Learning-based Approach for Vehicle-to-Vehicle Computation Offloading. *IEEE Internet Things J.* **2022**, *10*, 7244–7258. [[Google Scholar](#)]
- [5] Donta, P.K.; Srirama, S.N.; Amgoth, T.; Annavarapu, C.S.R. iCoCoA: Intelligent congestion control algorithm for CoAP using deep reinforcement learning. *J. Ambient Intell. Humaniz. Comput.* **2023**, *14*, 2951–2966. [[Google Scholar](#)] [[CrossRef](#)]
- [6] Li, J.; Shi, W.; Wu, H.; Zhang, S.; Shen, X. Cost-Aware Dynamic SFC Mapping and Scheduling in SDN/NFV-Enabled Space–Air–Ground-Integrated Networks for Internet of Vehicles. *IEEE Internet Things J.* **2021**, *9*, 5824–5838. [[Google Scholar](#)]
- [7] Wen, Z.; Garg, S.; Aujla, G.S.; Alwasel, K.; Puthal, D.; Dustdar, S.; Zomaya, A.Y.; Ranjan, R. Running industrial workflow applications in a software-defined multicloud environment using green energy aware scheduling algorithm. *IEEE Trans. Ind. Inform.* **2020**, *17*, 5645–5656. [[Google Scholar](#)]
- [8] Jiang, W. Software defined satellite networks: A survey. *Digit. Commun. Netw.* **2023**, in press. [[Google Scholar](#)] [[CrossRef](#)]
- [9] Elhattab, M.; Khabbaz, M.; Al-Dahabreh, N.; Atallah, R.; Assi, C. Leveraging Real-World Data Sets for QoE Enhancement in Public Electric Vehicles Charging Networks. *IEEE Trans. Netw. Serv. Manag.* 2023; early access. [[Google Scholar](#)] [[CrossRef](#)]
- [10] Donta, P.K.; Srirama, S.N.; Amgoth, T.; Annavarapu, C.S.R. Survey on recent advances in IoT application layer protocols and machine learning scope for research directions. *Digit. Commun. Netw.* **2022**, *8*, 727–744. [[Google Scholar](#)] [[CrossRef](#)]
- [11] Ravi, B.; Gautam, A.; Thangaraj, J. Stochastic performance modeling and analysis of multi service provisioning with software defined vehicular networks. *AEU-Int. J. Electron. Commun.* **2020**, *124*, 153327. [[Google Scholar](#)]
- [12] Ravi, B.; Thangaraj, J. End-to-end delay bound analysis of VANETs based on stochastic method via queueing theory model. In *Proceedings of the 2017 International Conference on Wireless Communications, Signal Processing and Networking*

- (WiSPNET), Chennai, India, 22–24 March 2017; pp. 1920–1923. [[Google Scholar](#)]
- [13] Wijesekara, P.A.D.S.N.; Gunawardena, S. A Machine Learning-Aided Network Contention-Aware Link Lifetime-and Delay-Based Hybrid Routing Framework for Software-Defined Vehicular Networks. *Telecom* **2023**, *4*, 393–458
- [14] Dustdar, S.; Murturi, I. Towards IoT processes on the edge. In *Next-Gen Digital Services. A Retrospective and Roadmap for Service Computing of the Future: Essays Dedicated to Michael Papazoglou on the Occasion of His 65th Birthday and His Retirement*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 167–178. [[Google Scholar](#)]
- [15] Dustdar, S.; Murturi, I. Towards distributed edge-based systems. In *Proceedings of the 2020 IEEE Second International Conference on Cognitive Machine Intelligence (CogMI)*, Atlanta, GA, USA, 28–31 October 2020; pp. 1–9. [[Google Scholar](#)]
- [16] Zhu, F.; Yi, X.; Abuadba, A.; Khalil, I.; Huang, X.; Xu, F. A Security-Enhanced Certificateless Conditional Privacy-Preserving Authentication Scheme for Vehicular Ad Hoc Networks. *IEEE Trans. Intell. Transp. Syst.* **2023**; early access
- [17] Siddiqui, S.; Hameed, S.; Shah, S.A.; Ahmad, I.; Aneiba, A.; Draheim, D.; Dustdar, S. Towards Software-Defined Networking-based IoT Frameworks: A Systematic Literature Review, Taxonomy, Open Challenges and Prospects. *IEEE Access* **2022**, *10*, 70850–70901. [[Google Scholar](#)]
- [18] Tahir, H.; Mahmood, K.; Ayub, M.F.; Saleem, M.A.; Ferzund, J.; Kumar, N. Lightweight and Secure Multi-Factor Authentication Scheme in VANETs. *IEEE Trans. Veh. Technol.* **2023**; early access. [[Google Scholar](#)]
- [19] Liu, Y.; Huo, L.; Wu, J.; Bashir, A.K. Swarm Learning-Based Dynamic Optimal Management for Traffic Congestion in 6G-Driven Intelligent Transportation System. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 7831–7846. [[Google Scholar](#)] [[CrossRef](#)]
- [20] Ameer, A.I.; Lakas, A.; Yagoubi, M.B.; Oubbati, O.S. Peer-to-peer overlay techniques for vehicular ad hoc networks: Survey and challenges. *Veh. Commun.* **2022**, *34*, 100455. [[Google Scholar](#)]
- [21] Imghoure, A.; Omary, F.; El-Yahyaoui, A. Schnorr-based Conditional Privacy-Preserving Authentication Scheme with Multisignature and Batch Verification in VANET. *Internet Things* **2023**, *23*, 100850. [[Google Scholar](#)]
- [22] Su, Y.; Huang, L.; Liwang, M. Joint Power Control and Time Allocation for UAV-Assisted IoV Networks over Licensed and Unlicensed Spectrum. *IEEE Internet Things J.* **2023**; early access. [[Google Scholar](#)]
- [23] Banoth, S.P.R.; Donta, P.K.; Amgoth, T. Target-aware distributed coverage and connectivity algorithm for wireless sensor networks. *Wirel. Netw.* **2023**, *29*, 1815–1830. [[Google Scholar](#)]
- [24] Alharthi, A.; Ni, Q.; Jiang, R.; Khan, M.A. A Computational Model for Reputation and Ensemble-Based Learning Model for Prediction of Trustworthiness in Vehicular Ad Hoc Network. *IEEE Internet Things J.* **2023**; early access. [[Google Scholar](#)] [[CrossRef](#)]
- [25] Mao, M.; Yi, P.; Zhang, J.; Wang, L.; Gu, Y.; Zhang, G. Roadside units plane optimization scheme in software-defined vehicular networks. *Trans. Emerg. Telecommun. Technol.* **2022**, *33*, e4499. [[Google Scholar](#)]
- [26] MalekiTabar, M.; Rahmani, A.M. A delay-constrained node-disjoint multipath routing in software-defined vehicular networks. *Peer-Netw. Appl.* **2022**, *15*, 1452–1472. [[Google Scholar](#)]
- [27] Sudheera, K.L.K.; Ma, M.; Chong, P.H.J. Real-time cooperative data routing and scheduling in software defined vehicular networks. *Comput. Commun.* **2022**, *181*, 203–214. [[Google Scholar](#)]
- [28] Ravi, B.; Thangaraj, J.; Petale, S. Stochastic network optimization of data dissemination for multi-hop routing in VANETs. In *Proceedings of the 2018 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, Chennai, India, 22–24 March 2018; pp. 1–4
- [29] R. Boutaba, M. A. Salahuddin, N. Limam, S. Ayoubi, N. Shahriar, F. Estrada-Solano, O. M. Caicedo, A comprehensive survey on machine

- learning for networking: evolution, applications and research opportunities, *Journal of Internet Services and Applications* 9 (16). doi:10.1186/s13174-018-0087-2.
- [30] U. of California, Knowledge discovery and datamining cup 1999 data, <https://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html>, accessed on July 2020 (1999).
- [31] M. Tavallae, E. Bagheri, W. Lu, A. Ghorbani, A detailed analysis of the kdd cup 99 data set, IEEE Symposium. Computational Intelligence for Security and Defense Applications, CISDA 2. doi:10.1109/CISDA.2009.5356528.
- [32] NSL-KDD dataset, <https://www.unb.ca/cic/datasets/nsl.html>, accessed on July 2020 (2009).
- [33] L. Boero, M. Marchese, S. Zappatore, Support vector machine meets software dened networking in ids domain, in: 29th International Teletra-c Congress, Genoa, Italy, 2017, pp. 25-30.
- [34] P. Sangkatsanee, N. Wattanapongsakorn, C. Charnsripinyo, Practical real-time intrusion detection using machine learning approaches, *Computer Communications* 34 (18) (2011) 2227-2235. doi:https://doi.org/10.1016/j.comcom.2011.07.001. URL <http://www.sciencedirect.com/science/article/pii/S014036641100209X>
- [35] P. S. Bithas, E. T. Michailidis, N. Nomikos, D. Vouyioukas, A. G. Kanatas, A survey on machine-learning techniques for uav-based communications, *Sensors* 19 (23). doi:10.3390/s19235170. URL <https://www.mdpi.com/1424-8220/19/23/5170>
- [36] H. Sedjelmaci, S. M. Senouci, N. Ansari, A hierarchical detection and response system to enhance security against lethal cyber-attacks in uav networks, *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 48 (9) (2018) 1594-1606. doi:10.1109/TSMC.2017.2681698.
- [37] J. McCoy, D. B. Rawat, Software-dened networking for unmanned aerial vehicular networking and security: A survey, *Electronics* 8 (2019) 1468. doi:10.3390/electronics8121468.