computers

MDPI

*Article*

# Stochastic Modeling for Intelligent Software-Defined Vehicular Networks: A Survey

**Banoth Ravi [1], Blesson Varghese [2], Ilir Murturi [3,*], Praveen Kumar Donta [3,*], Schahram Dustdar [3], Chinmaya Kumar Dehury [4] and Satish Narayana Srirama [5,*]**

1 Department of Electronics and Communication Engineering, Indian Institute of Information Technology Tiruchirappalli, Tiruchirappalli 620012, Tamil Nadu, India; ravib@iiitt.ac.in
2 School of Computer Science, University of St Andrews, Andrews KY16 9SX, UK; bv6@st-andrews.ac.uk
3 Distributed Systems Group,Technische Universitat Wien, 1040 Vienna, Austria; dustdar@dsg.tuwien.ac.at
4 Mobile & Cloud Lab, Institute of Computer Science, University of Tartu, 50090 Tartu, Estonia; chinmaya.dehury@ut.ee
5 School of Computer and Information Sciences, University of Hyderabad, Gachibowli, Hyderabad 500032, Telangana, India
* Correspondence: imurturi@dsg.tuwien.ac.at (I.M.); pdonta@dsg.tuwien.ac.at (P.K.D.); satish.srirama@uohyd.ac.in (S.N.S.); Tel.: +43-1-58801-58413 (I.M.); +43-1-58801-18432 (P.K.D.)

**Abstract:** Digital twins and the Internet of Things (IoT) have gained significant research attention in recent years due to their potential advantages in various domains, and vehicular ad hoc networks (VANETs) are one such application. VANETs can provide a wide range of services for passengers and drivers, including safety, convenience, and information. The dynamic nature of these environments poses several challenges, including intermittent connectivity, quality of service (QoS), and heterogeneous applications. Combining intelligent technologies and software-defined networking (SDN) with VANETs (termed intelligent software-defined vehicular networks (iSDVNs)) meets these challenges. In this context, several types of research have been published, and we summarize their benefits and limitations. We also aim to survey stochastic modeling and performance analysis for iSDVNs and the uses of machine-learning algorithms through digital twin networks (DTNs), which are also part of iSDVNs. We first present a taxonomy of SDVN architectures based on their modes of operation. Next, we survey and classify the state-of-the-art iSDVN routing protocols, stochastic computations, and resource allocations. The evolution of SDN causes its complexity to increase, posing a significant challenge to efficient network management. Digital twins offer a promising solution to address these challenges. This paper explores the relationship between digital twins and SDN and also proposes a novel approach to improve network management in SDN environments by increasing digital twin capabilities. We analyze the pitfalls of these state-of-the-art iSDVN protocols and compare them using tables. Finally, we summarize several challenges faced by current iSDVNs and possible future directions to make iSDVNs autonomous.

**Keywords:** Internet of Things; vehicular ad hoc networks; software-defined networks; intelligent digital twin networks; stochastic modeling and performance evaluation



**Citation:** Ravi, B.; Varghese, B.; Murturi, I.; Donta, P.K.; Dustdar, S.; Dehury, C.K.; Srirama, S.N. Stochastic Modeling for Intelligent Software-Defined Vehicular Networks: A Survey. *Computers* **2023**, *12*, 162. https://doi.org/10.3390/computers12080162

Academic Editor: Kannan Govindarajan

Received: 11 July 2023
Revised: 8 August 2023
Accepted: 10 August 2023
Published: 12 August 2023



## 1. Introduction

A vehicular communication system broadcasts information about vehicles so that traffic chaos, congestion, and accidents are avoided. However, congestion is a more significant problem. Vehicle applications demand stringent QoS and unprecedented network capacity in internet technology. Vehicle applications have limited task-offloading schemes and flexibility issues [1]. The Base Station (BS) and Road-Side Units (RSUs) cooperate in task-offloading problems while dynamically adapting to current network environments. This enhances QoS in VANETs [2]. Link connectivity changes frequently based on vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) distances due to high mobility in a VANET system [3]. The packet is forwarded through vehicles using internet services modeled in a queueing network for data dissemination [4]. Heterogeneous vehicular networks and software-defined networking (SDN) are used to reduce traffic congestion [5] and improve network performance in VANETs [6,7]. The main objective of VANET and SDN connectivity is to separate the control plane and data plane [8]. The purpose of SDN in wireless and ad hoc domains is to centralize network services, control, and flexibility, which has gained attention over the last few decades, as shown in Figure 1.

This survey discusses how SDN technologies can be a promising solution to the challenges in vehicular networks while providing access to emergency services and high-bandwidth applications with low latency. Mobility management is a critical component of vehicular networks, with location management protocols, processes, and handoff management schemes being the key areas of concern [9]. The survey presents comprehensive mobility management in SDN-enabled vehicular networks, including models, challenges, and solutions. Mobility management solutions can be classified according to the vehicular network model used, such as SDN-based, HetNet-based, fog-based, and hybrid solutions [10]. The survey provides insights for young researchers in the field of intelligent VANETs to understand the implications and directions for futuristic wireless networks. The survey also discusses how traffic prediction in VANETs can be improved by using a stochastic vehicular mobility model that accounts for realistic variations in inter-vehicle communication over consecutive time steps [11,12].

A VANET is a wirelessly connected mobile vehicle network in the transportation sector. The frequent failures in VANETs make it difficult to disseminate information. High mobility and isolated nodes result in topology changes, which represent a major challenge in VANETs. The SDVN paradigm is the SDN concept incorporated into VANETs, which overcomes the previous challenges of SDVNs. It consists of a logically centralized control plane that analyzes the data in the vehicular network and makes network decisions, thus enhancing the programmability and flexibility of the vehicular network [13].

Traditionally, networking has been infrastructure-based, with the control plane spread throughout many routers. SDN logically isolates the fundamental network control mechanism from switches and routers to provide network control centralization [14]. With SDN, the controller gathers information about the status of the network, allowing the controller to design safe paths that are in line with the network's requirements and provide a better level of network awareness than with conventional hardware-driven networking. In SDN, there are three planes: the infrastructure plane, the control plane, and the application plane. The main advantages of SDVNs over conventional networks are flexibility and programmability. Using a single protocol, physical devices can communicate with each other via SDN, which allows control to be centralized. SDN has allowed us to perform and provide tasks such as traffic optimization, network virtualization and automation, and cloud-based service coordination. Due to the fact that the SDN controller is often the point of failure, dependability is one of the significant drawbacks of SDN. Moreover, SDN has difficulties integrating with traditional networks, which cannot utilize OpenFlow; the centralized controller cannot independently manage all traffic, and there are only a few protocols for communication between the controller and applications [13].

The SDVN is a variant of the software-defined wireless network (SDWN) among wireless networks. The SDVN architecture makes vehicular networks adaptable and versatile by integrating SDN into VANETs [11]. The network perception provided by SDN controllers enables numerous benefits, including adaptive node transmission power reservation, improved routing, and flexible radio interface placement. Due to the collection of network statistics, the SDVN improves networking functions, such as routing and load balancing, and enables global optimization in VANETs. It also promotes network innovation by enabling VANET technologies to be evaluated and implemented at a lower cost. As a result of the extensive mobility of the network nodes, as well as the changeable topology of the network, the SDVN encounters some difficulties, including security gaps and complex network operations, such as routing and transmission management [13].

The rapid advancement of V2V and V2I communication technologies has made intelligent software-defined vehicular networks (iSDVNs) increasingly important. Intelligent Transportation Systems (ITSs), such as traffic management, collision avoidance, and autonomous driving, cannot function properly without efficient and reliable vehicle-to-vehicle and vehicle-to-infrastructure communications, and vice versa [15]. A mathematical approach to analyzing and predicting the behavior of systems with random variables, stochastic modeling, has emerged as a promising tool for designing and assessing intelligent SDVNs [14]. This survey aims to present the state-of-the-art stochastic modeling techniques and their applications in iSDVNs as some implications and possible research in the near future. This survey also highlights the significant challenges of VANETs, including limitations on data dissemination, connectivity, load buffering, network congestion, and multi-hop routing, and how queueing networks, intelligent SDVNs, and software-defined heterogeneous vehicular networks (SDHVNs) can be used to address these challenges.

A fundamental change in network management has been made with SDN, which offers flexibility, programmability, and centralized control. However, it is challenging for network administrators to understand and efficiently manage the network state because SDN architectures are dynamic and distributed. On the other hand, digital twin technology has shown great promise in a number of domains, enabling the virtual representation of physical entities, systems, or processes. We aim to enhance network management by providing actionable insights and real-time intelligence by integrating digital twin technology and SDN. Digital twins are virtual representations of network infrastructure, applications, and services interconnected through SDN. The virtual model comprises network components like switches, routers, controllers, and individual packets and flows. The digital twin is created by collecting and integrating real-time data from the physical network to create a comprehensive and current view of the entire SDN ecosystem. By analyzing historical trends, administrators can gain insight into the current state of the network, predict potential issues, and determine key performance bottlenecks, as illustrated in Figure 1.

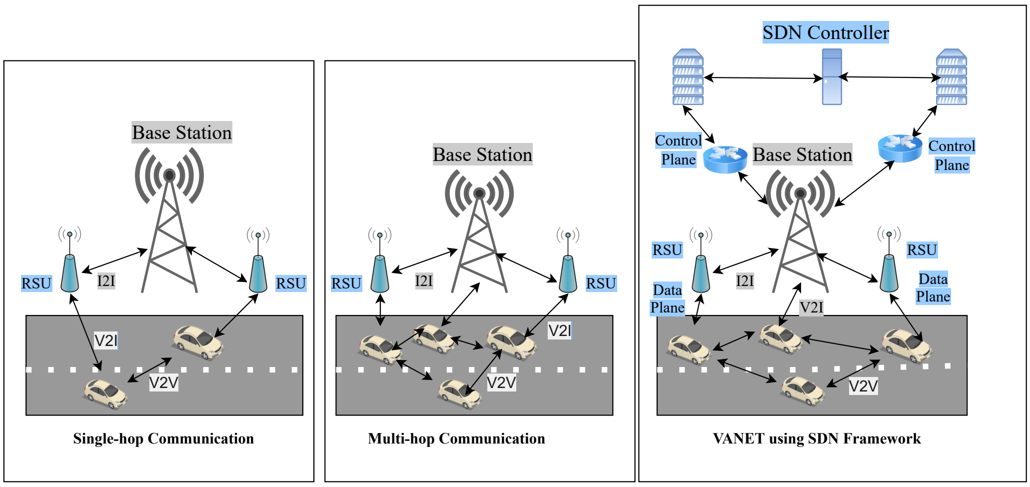


**Figure 1.** The SDVN architecture [16].

### 1.1. Motivation for This Survey

SDN has become an increasingly popular approach to network architecture, enabling additional flexibility and programmability in network management [17]. In the context of VANETs, SDN has the potential to improve network performance and efficiency by providing a centralized controller to manage network traffic and resources. However, while there have been many surveys on SDN and VANET separately, there is currently a lack of comprehensive surveys on the intersection of these two fields [18]. This survey aims to fill that gap by providing state-of-the-art literature on SDN for VANETs. Specifically, in this survey, we examine the various use cases and architectures of SDN in VANETs and the challenges and opportunities presented by this intersection. Here, we also analyze the existing survey papers in this area and identify the gaps and limitations in the current research. To differentiate this survey from existing surveys, we focus specifically on the intersection of SDN and VANETs, rather than simply offering a general overview of SDN or VANETs [19]. Additionally, we provide a more comprehensive and up-to-date analysis of the existing literature in this field and identify potential future research directions. Ultimately, this survey provides a valuable resource for researchers and practitioners working with SDN and VANETs [20].

This survey discusses the challenges of traffic accidents and highway congestion and the need to optimize resource allocation techniques to improve the QoS in VANETs [21]. Information technology and ITSs can be used to improve traffic efficiency in VANETs [22]. Mobility-prediction-based routing protocols and multi-hop communication can provide network stability and reliability for the high dynamic flow of vehicles in VANETs. Network connectivity [23] is controlled by RSUs and BSs for traffic safety and efficiency [24,25]. The survey also emphasizes the importance of the accurate stochastic modeling of multi-hop routing and cooperative data dissemination to enhance transportation and increase QoS [26–28]. Finally, the survey suggests using multi-hop cooperative data dissemination methods to improve system performance and resource utilization in VANETs [29]. The performance of SDN scenarios in VANET systems depends on optimal traffic load balancing. In the VANET system, an analysis of enhanced reliability of service (eRELSERV)-SDVN is needed based on queueing theory. Vehicular networks are ad hoc and, therefore, challenging to manage due to the random connection of end-to-end network devices. Integrating SDN with a VANET brings programmability and flexibility to the vehicular network, improving its performance [30].

The SDN controller can manage packet flow-table performance through the OpenFlow protocol, which helps handle heavy traffic flow in VANET communications and potentially prevent link breaks. A queueing analysis is also valuable for estimating SDN and managing high arrival and service demands. This can enable upcoming V2V and V2I services and simplify vehicular network optimization and mobility management. The SDHVN system uses queueing theory to provide optimal packet scheduling for efficient resource utilization among V2V and V2I communications in VANETs [31]. It improves the QoS of packet scheduling and enhances network utility while reducing traffic casualties. The intelligent digital twin (IDT) is a promising technique for simulating intelligent networking models. It can be used to observe and understand current and historical data to enhance routing efficiency, maintenance, traffic flow, and security in the physical network [32].

This survey acknowledges current research in software-defined vehicular networks (SDVNs) and identifies challenges and limitations in implementing SDN. The survey does not introduce new concepts or solutions but provides a comprehensive overview of existing techniques. It analyzes their strengths and weaknesses and identifies research opportunities. This survey synthesizes existing knowledge and presents it in an organized manner, making it a valuable resource for researchers and practitioners. In addition to providing a baseline understanding of the state of the art, it highlights gaps in the literature and suggests future directions. Studies and surveys need not introduce entirely new concepts or solutions to be valuable. Surveys consolidate existing knowledge, identify trends, and guide future research. SDVNs as a field will be advanced by building upon and refining existing approaches. So, in this survey, we are not introducing groundbreaking new research, but we do analyze and synthesize the existing research.

### *1.2. Organization*

This survey is organized as follows. First, we introduce SDN and VANETs, including their characteristics and the motivation for their intersection. Next, we provide a discussion about the survey method within which we provide both inclusion and exclusion criteria, along with the objectives of the proposed survey. In the next section, we provide the background of SDVNs. After this, we integrate the iSDVN into the VANET system model. Further, we provide a detailed discussion about the performance evaluation of iSDVNs.

In the next section, we present open issues. Finally, we present our conclusions and recommendations for future research directions. We summarize all the abbreviations used in this paper in Abbreviations.

## 2. Survey Method

In order to conduct performance benchmarking research on SDVNs, it is important to have a clear understanding of the criteria used to select relevant surveys. Here are some possible inclusion and exclusion criteria for this type of research:

### *2.1. Inclusion Criteria*

The inclusion criteria were as follows:

- Surveys must be related to SDVNs and network performance benchmarking.
- Surveys must have been published in peer-reviewed academic journals or conference proceedings.
- Surveys must have been published within a certain time frame (e.g., last five years) to ensure that the research is current.
- Surveys must have used empirical research methods (e.g., experiments, simulations, case studies) to collect and analyze data.

### *2.2. Exclusion Criteria*

The following were excluded from this survey:

- Surveys that are not related to SDVNs or network performance benchmarking;
- Surveys that are not published in peer-reviewed academic journals or conference proceedings;
- Surveys that are published outside the time frame specified;
- Surveys that did not use empirical research methods.

Scientific databases specialize in different subject areas and types of publications. We selected databases with comprehensive coverage based on the research domain or topic of interest. Databases can be categorized according to the fields that they cover or their data types. Choosing surveys that meet these criteria was based on a systematic search of the literature using different databases (e.g., PubMed, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect, Scopus, Google Scholar, and others, depending on the field of study and the research objectives, were considered) with appropriate search terms and filters. Additionally, citation tracking and reference list searches can be used to identify additional relevant surveys. After identifying potential surveys, a screening process can be used to determine which surveys meet the inclusion and exclusion criteria. The possible overall sample data collection is shown in Figure 2.

As part of next-generation networking technologies, such as 5G, the Internet of Things, fog/edge computing [33,34], wireless/mobile networks, Network Function Virtualization (NFV), sensor networks, IDT, and VANET, SDN has also gained importance in recent years [35]. As compared with existing surveys, the key contributions of this survey are summarized as follows: 1. This survey covers the latest advances in architectures, essential techniques, and solutions for software-defined vehicular networks. 2. We present current implications, future scope or opportunities to explore, and simulation tools that can be discussed or applied in future research. Several dimensions are used to compare and contrast our work with existing surveys on VANETs, IDT, and the controller placement problem (CPP) in SDN. We analyze each survey from a variety of perspectives, including modeling choices, objectives, techniques, and evaluation metrics. We also discuss how SDN might be used in a variety of upcoming networking paradigms. The scope of this survey and future research directions are shown in Table 1, Figure 3 summarizes the focus of our survey, and Figure 4 shows the taxonomy of the organization of iSDVN.

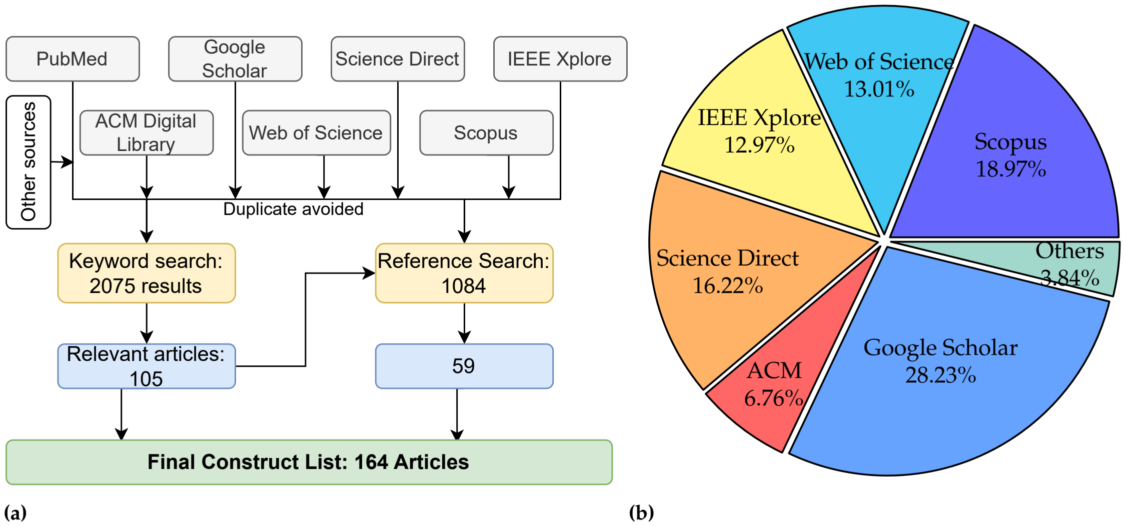


**Figure 2.** The whole process of collecting samples for a database. (**a**) Review construction for inclusion and elimination of papers (after eliminate duplicates). (**b**) Percentage of papers considered from various scientific databases (before eliminate duplicates).

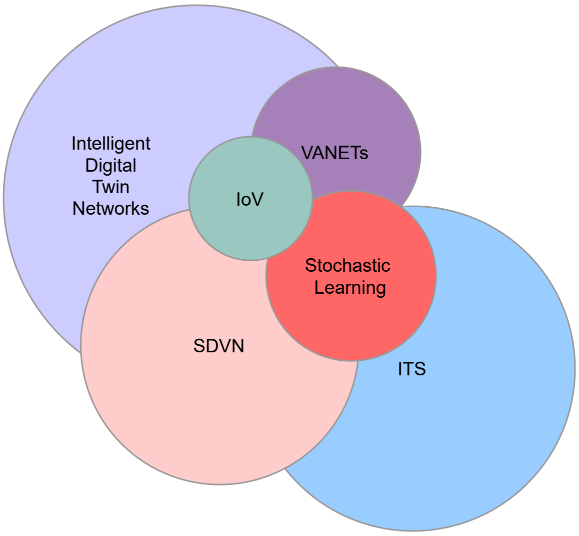


**Figure 3.** The scope of our survey and future research directions.

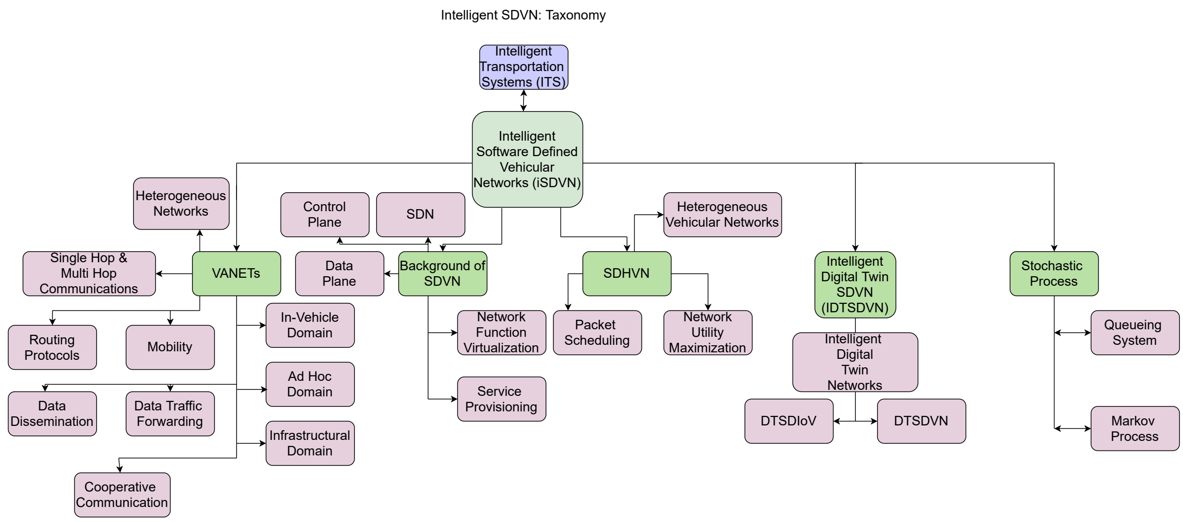


**Figure 4.** Taxonomy of the organization of this iSDVN.

**Table 1.** Comparison of recent and related surveys on SDVN-related architecture.

| Reference | Year | Communication | Infrastructure | Interface | Stochastic Modeling | Performance Analysis | Cooperative Communication | Data Dissemination | Mobility | Routing | Resource Utilization | End-to-End Delay | SDVN | iSDVN | IDTSDVN | Others | Remarks |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [36] | 2016 | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | 1. SDVN-related open issues are not discussed. 2. The latest advances in DD and CC are not covered. |
| [37–40] | 2016 | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ | ✓ | The focus of the survey is more on QoS and less on SDN and IoV applications. |
| [12,41–43] | 2017 | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | ✓ | ✓ | ✗ | ✓ | ✓ | ✓ | ✗ | ✗ | ✓ | 1. Covers issues related to SDN and VANET. 2. Focuses on some but not all protocols for intelligent networks. |
| [44] | 2017 | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | ✓ | ✓ | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ | ✓ | Without recent advancements in IDT, this survey covers delay minimization in radio access networks. |
| [45–49] | 2018 | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✓ | In SDVNs, multicast communication improves SDVN utility performance and reduces frequency resource consumption. |
| [2,50,51] | 2018 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ | 1. The benefits of traditional SDVNs are described in these surveys. 2. IDTSDVN's recent advancements are not discussed. 3. There are no open issues for IDTNs. |
| [52–55] | 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ | ✓ | The survey describes the heterogeneous issues of dissemination and cooperation in SDVNs. |
| [56–59] | 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ | ✓ | These surveys examine the side effects of delay and reliability in network selection by applying network utility functions and queueing theory. |
| [60–64] | 2020 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | The study focused on IDTSDVN and SDVN, but it did not cover all other elements, such as QoS, reliability, delay, and PDR. |
| [65–67] | 2020 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✓ | ✓ | ✓ | ✗ | ✓ | ✓ | Experimental evaluation was performed on VANETs, SDVNs, iSDIoVs, and IDTSDVNs in various conditions. |
| [68–73] | 2021 | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✓ | ✓ | ✗ | ✓ | ✓ | ✓ | ✗ | ✓ | ✓ | In VANETs, IoV, SDVN, and IDTSDVN, deep reinforcement learning and digital twins were compared in various conditions. |
| [74–82] | 2022 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ | ✓ | Machine learning and deep reinforcement learning were compared in various VANET, IoV, and SDVN scenarios. |
| [19,31,83–87] | 2023 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✓ | ✓ | Heterogeneous scenarios, routing, data collection and optimization, data dissemination, digital twins and deep reinforcement learning were compared in various VANET, IoV, SDVN, ISDVN, and IDTSDVN, Aeronautical Ad Hoc Networks in Beyond 5G scenarios. |
| **Our Survey** | – | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | With the iSDVN architecture, data delivery is improved by reducing traffic congestion and reducing latency. Stochastic learning research advances, challenges, and scope for ZTP, ITS, VANETs, IoV, SDVN, iSDVN, and IDTSDVN at the data link, network, and application layers. |

## 2.3. Objectives

The main objective of this survey is to present stochastic models for providing intelligent multi-hop cooperative data dissemination in software-defined vehicular communication systems for better network performance. Increasing traffic safety and improving the quality of service would be possible with an intelligent SDN system. In addition, the multi-hop vehicular connectivity enables the forwarding mechanisms to operate with minimal topology knowledge and dynamically respond to network topology changes. In this survey, we focus on the following objectives:

- The first objective of our study is to investigate and improve QoS strategies in SDVNs. As highway traffic density increases and vehicles become increasingly mobile, queueing models for vehicular traffic have to be developed in order to predict vehicles' mobility based on their traveling time, behavior, and speed on the highway and to avoid collisions using routing protocols and scheduling in iSDVNs.
- Afterward, we intend to assess how data traffic forwarding improves efficient resource allocation, minimizes delay and packet loss, and optimizes flow control in vehicular networks using a stochastic approach.
- Next, we present a model to enhance iSDVN service reliability by considering how intermittent connectivity affects V2V and V2I network connectivity control and management. A multi-hop cooperative data dissemination protocol is proposed in order to reduce packet loss, improve connectivity, utilize network resources more effectively, and increase reliability.
- Afterward, we propose a model of heterogeneous vehicular networks via SDN and multi-hop cooperative data dissemination schemes to highlight the improvements that can be made via SDN in heterogeneous vehicular networks.
- Finally, the network traffic and resource utilization can be accurately modeled using a digital twin (DT). Administrators can use simulations and "what-if" scenarios to optimize network efficiency and make resource allocation, bandwidth provisioning, and routing decisions.

The objective of the survey is to provide an overview of stochastic modeling techniques used for intelligent SDVNs. The study aims to demonstrate how stochastic modeling can be used to address various challenges in SDVNs, such as resource allocation, routing, and QoS provisioning. The survey also aims to highlight the benefits and limitations of different stochastic modeling techniques and provide insights into future research directions in this area.

## 3. Background: iSDVN System

An intelligent SDVN is a type of network architecture that uses software to manage and configure network components such as switches, routers, and other networking hardware. An SDVN is designed to be more flexible and adaptable than traditional networks, making it easier to manage and modify when the network needs to change [77]. The SDVN architecture consists of a centralized controller that manages the network's data plane and control plane. The controller interacts with network switches and other devices through APIs and protocols such as OpenFlow to configure and control network traffic. One of the key benefits of an SDVN is that it enables network administrators to separate the control plane from the data plane, which can improve network performance and reduce congestion [78]. Additionally, an SDVN provides a more programmable and automated network environment, making it easier to manage network resources and respond to changes in network traffic [31]. Given these benefits, performance benchmarking research is an important area of study for SDVNs. By comparing the performance of different SDVN architectures, researchers can identify best practices and areas for improvement, ultimately leading to more effective and efficient network designs [19].

### 3.1. Single-Hop and Multi-Hop Network Connectivity in SDVNs

Single-hop connectivity refers to direct connectivity from source to destination nodes without intermediate nodes. Here, packets are transmitted directly to the destination node with minimum delay, as there are no intermediate nodes between the source node and the destination node, as shown in Figure 1. The apparent benefit of single-hop connectivity in a VANET is that there will be direct vehicle-to-vehicle communication, ensuring low latency [88]. But, the limitation of single-hop connectivity is the limited transmission range. When the source node and destination node are far apart, with the limited transmission range of single-hop networks, data traffic must be routed to the destination over a number of hops through intermediate nodes to reach its destination node.

A multi-hop network with intelligent message broadcasting can reduce the burden on the communication channel, as shown in Figure 1. Also, multi-hop routing could significantly improve network capacity and throughput in wireless networks. In VANETs, most of the safety-related information is broadcasted to all nodes in the network, thereby increasing the traffic congestion in the network [89]. However, researchers have proposed multi-hop routing protocols to resolve the problem of congestion in VANETs.

### *3.2. Mobility*

In SDVNs, moving vehicles communicate through distributed, self-organizing networks. Even high-speed vehicles can be connected to an SDVN. Due to the high-speed motion of vehicles, SDVNs are inefficient or unusable. Changing direction and speed on the road creates an increasingly dynamic environment for network topology [47]. Hence, the network protocol and vehicular mobility must have a strong interaction due to these circumstances. In SDVNs, data traffic may impact mobility as well due to the dynamic change in the network topology. Wireless communications and mobility have a bidirectional relationship [90]. Integrating communication protocols and modeling mobility into vehicular networks has taken a lot of effort from researchers. The majority of SDVN protocols are designed to optimize data traffic as well as mobility.

### *3.3. Routing*

The four types of routing can be described as follows: unicast routing, multicast routing, broadcast routing, and geocast routing [10,91]. One-to-one communication describes SDVN unicast routing, which routes packets between a source and a destination node. SDVNs use multicast routing to send packets from one source to a group of nodes, also known as grouping or one-to-many routing [92]. Multicasting is widely used in defense and military applications. In this routing type, packets are broadcast across the network from a source node to multiple target nodes connected to the network. It is a popular method of ensuring human safety during disasters. Packets can be geocast to a set of nodes within a particular geographical region or geocast area using geocast routing. Geocast group members are identified by location in a geographic area, while membership in a multicast group can occur anywhere in an ad hoc network [93]. To reduce latency between nodes in an SDVN, researchers have developed several routing protocols, which are categorized as follows:

1. *Position-based routing protocol*—Using the Global Positioning System (GPS) and the destination IP address, the source node routes a packet using the destination's geographical location and IP address.
2. *Topology-based routing protocol*—In this protocol, packets are forwarded from the source to the destination node based on network connectivity information. Proactive routing methods, reactive routing methods, and hybrid routing methods are three types of proactive routing.
    (a) *Proactive routing:* For this protocol, the shortest-path algorithm determines the path and stores it in the routing table. During periodic updates, this table is shared with neighbors.
    (b) *Reactive routing:* Route discovery begins when a node discovers that it needs to communicate with another node. This is called "on-demand routing." This protocol has the advantage of reducing network traffic.
    (c) *Hybrid routing:* In this protocol, networks are classified as local or global, and proactive and reactive routing methods are combined to reduce routing overhead and delay for local and global networks.

3. *Broadcast-based routing protocol*—In the broadcast domain, broadcast routing sends packets to every node in the vehicular network.
4. *Cluster-based routing protocol*—For communication purposes, clusters are created in a network based on parameters such as velocity and direction. The cluster head manages inter-cluster and intra-cluster communication. The cluster head creates a virtual network infrastructure to enable scalability when performing intra-cluster communication using a direct path.
5. *Geocast-based routing protocol*—A mobicast message is used to communicate between vehicles in a region termed the *zone of relevance*.

### 3.4. Routing in a Multi-Access Environment with Learning Approaches

Routing is an important aspect of SDN and VANETs, as it determines how packets are routed from their source to their destination. VANETs may utilize heterogeneous wireless technologies in multi-access environments, including DSRC, IEEE 802.11p, cellular networks, and wireless LANs [94].

SDN and VANET routing usually uses learning approaches to improve efficiency and adaptability based on varying conditions and dynamic network conditions. Routing in SDN and VANETs commonly uses the following learning techniques:

1. *Reinforcement Learning*—In reinforcement learning (RL), agents learn by interacting with the environment to make decisions. According to the observed performance of different routes over time, RL can be used in SDN and VANETs to adapt routing decisions. As a result, the network can learn which routes are more reliable, have lower latency, or have a higher throughput.
2. *Deep Learning*—By using deep-learning techniques, such as neural networks, we can identify patterns and correlations in SDN and VANET data that traditional routing algorithms would not detect. The trained models can support better routing decisions, especially in dynamic and complex SDN and VANET scenarios.
3. *Context-Aware Routing*—The concept of context-aware routing involves making routing decisions based on various contextual factors, such as vehicle speed, traffic density, and link quality. Routing metrics can be dynamically adjusted using machine-learning algorithms based on the current context, improving route selection.
4. *Federated Learning*—The privacy and security of SDN and VANETs are crucial considerations. A federated learning system enables vehicles to train a model without sharing raw data with a centralized entity [95]. This approach can enhance routing decisions while protecting individual vehicle privacy.
5. *Online Learning*—In SDN and VANETs, routing algorithms have to be capable of quickly adapting to changing conditions due to their dynamic nature. Since online learning can be applied to VANETs, where the network topology can change rapidly, online learning techniques are suitable for continuously updating routing decisions.

Using these learning approaches, multi-access VANETs can significantly improve routing efficiency, reliability, and adaptability. Learning-based routing algorithms pose a number of challenges, including computational overhead, scalability, and security concerns. Real-world testing and validation are also crucial for these approaches to be effective and robust in dynamic vehicular scenarios.

### 3.5. Data Traffic Forwarding

The amount of data flowing through a network at any given moment is known as data traffic. Network traffic measurement is based on the amount of data available in the network. Communication between RSUs is a key component of SDVNs. By sending data traffic via moving vehicles, remote RSUs communicate with the central RSU without using the backbone network [96]. All buffered data traffic is passed from a source RSU to a destination RSU when a vehicle is selected to assist. The source RSU can violate the delay bound while the destination RSU transfers data. Data traffic that violates bound delays is expected to make up a relatively small percentage of all data traffic [97]. Consider a scenario where a lot of data traffic is delayed. To deliver buffered data traffic to the source RSU, another system (for example, cellular communications) is required.

### 3.6. Data Dissemination

Vehicles may gather and disseminate data to big data repositories, such as current location, speed, and road density [98,99]. As a result, adjacent vehicles collect data on road and surrounding conditions and reduce their speed to avoid future accidents [100]. One-hop and multi-hop communications can be used to disseminate data [29]. High latency in high-traffic areas can impact the performance of data distribution networks [101]. An SDVN has its inherent features, making it difficult to establish a secure and effective data dissemination scheme [85]. Random mobility, rapid topology changes, link partitions, or network fragmentation also occurs in the vehicular environment at nodes. Vehicles in random mobility patterns are considered for data dissemination in SDVNs. This would significantly affect data delivery, quickly contributing to severe packet failures. In addition, scalability will be increased by forwarding data packets between two-way nodes using multiple hops for the wireless radio spectrum of RSU [102]. Through SDN, VANETs can disseminate data effectively and efficiently [103].

### 3.7. Cooperative Communication

SDVNs are aimed at bringing safety and smoothness to the transport system. They can support transportation management and cooperative safety by allowing V2V and V2I connectivity [104]. Vehicles can regularly broadcast safety-related details, e.g., location, speed, heading, and neighbors, through the shortest routes from the source node to the destination node, so-called cooperative communication. Cooperative communication achieves cooperative safety, providing the required means to establish cooperative awareness in the situation [105]. The sharing of real-time data requires connectivity and cooperation between routes. In SDVN communication, we face challenges like frequent link failures and high-mobility issues. Using cooperative communication within the vehicular network, these challenges are reduced, and reliability is improved. Hence, nodes are allowed to cooperate with each other [48]. Next, we focus on various technologies in the field of SDVNs.

### 3.8. Resource Optimization

Digital twins are being used to optimize resources through various applications that utilize digital twins' (DTs) capabilities to improve efficiency, productivity, and decision making. In addition to enabling the real-time monitoring, analysis, and simulation of their physical counterparts, digital twins allow the real-time analysis and monitoring of non-digital objects. Digital twins provide numerous benefits when applied to resource optimization by providing valuable insights and predictive capabilities. Modeling network traffic and resource utilization is made more accessible with DTs. Administrators can simulate and run "what if" scenarios to optimize resource allocation, provisioning, and routing decisions for improved network efficiency.

## 4. Integrating into VANET System Model for iSDVN

As a result of this survey on iSDVNs, the following challenges have been identified.

SDN provides a way to integrate large-scale wireless networks, such as vehicular networks and ITSs, among others [106]. The data plane and the control plane are separated in SDN. A decoupled forwarding plane provides efficiency, and flexibility makes forwarding devices available at forwarding plane nodes. The control plane provides flow rules and management information about packet forwarding to the data plane [11]. For SDN control plane and data plane communication, OpenFlow is the most commonly used protocol, as shown in Figure 5. In a VANET, planes can communicate with other vehicles, RSUs, and BSs via the OpenFlow protocol. An SDN controller can also facilitate communications between BSs and RSUs [41,60].

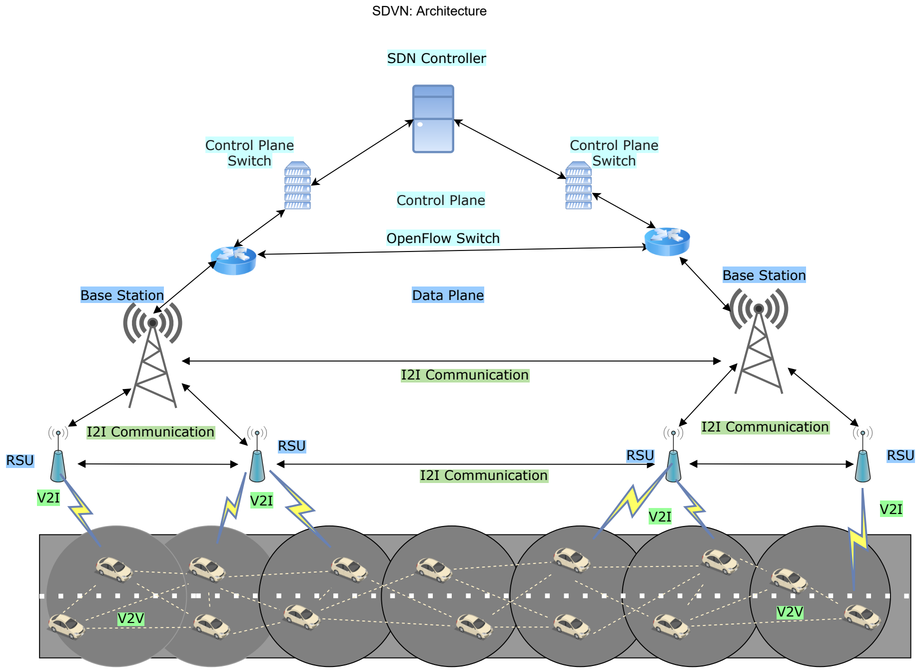


**Figure 5.** The general architecture for iSDVN.

VANETs' network topologies change constantly due to their mobility, thus making it difficult for the control plane to maintain vehicle location, thereby increasing the overhead for SDN management. The overhead issue can be overcome by integrating SDN with VANET technologies. Figure 5 shows an illustration of an SDVN. It improves the network performance and QoS [44]. In VANETs, SDN is utilized to calibrate packet- and network-level parameters [42]. The SDVN provides network resources for V2V communication through a logically centralized controller [37]. The SDN control plane also supports wireless data dissemination, further increasing the transmission range. In a dynamic network topology, maintaining network connectivity is extremely challenging. For network connectivity problems, an SDVN may provide the solution [107]. SDVN controllers face another challenge in queue management, especially during packet failure conditions [68]. As a result of excess packets flowing in the queue, the waiting time increases, impacting the overall performance of the SDVN. In an iSDVN, we can use queueing models to reduce controller response times in queues, improving its performance.

### *4.1. Systems under Test*

In this section, the systems under test in iSDVN performance benchmarking are examined by considering two components, infrastructure and infrastructure-less, which are discussed in the following subsections. Many performance benchmarks are evaluated on the EstiNet OpenFlow network simulator and emulator and OMNeT discrete event simulator. *Control Plane:*In SDN, network intelligence is logically centralized in software-based controllers (i.e., control plane). Server decisions determine how the network nodes will forward data packets. In the centralized implementation, vehicles do not need to maintain any control information [37,38]. The control plane maintains switches and routers that deal with connectivity and data forwarding. In transmission, this applies to both single-hop and multi-hop scenarios. The iSDVN architecture provides network protocol management through a logical central controller. Registration should be permitted for each device, including the OBU, and for vehicles as well. Controller status reports, including the position and volume of data, are provided periodically. Based on the information collected, it is determined how to reconfigure network protocols and their control parameters and how to distribute and exchange network resources. By doing so, the network can maximize its performance.

*Data Plane*: During RSU communications, data traffic is forwarded to vehicles through the data plane. A data plane and overlay network are established to eliminate heterogeneity in the vehicular scenario. SDN provides a network management tool by abstracting vehicles, RSUs, and BSs as switches. Depending on its mobility, an SDN switch can be divided into mobile and stationary data planes. RSUs are regarded as mobile data planes, and BSs are referred to as stationary data planes. Different policies are applied to data plane management [37]. To transmit data effectively, an iSDVN uses V2V and vehicle-to-RSU communication links [108]. Multi-hop V2V transmissions to distant destinations that are not covered by RSUs can be carried out using connections.

*Network Function Virtualization*: An important aspect of Network Function Virtualization (NFV) is segmenting network node functions into functional blocks [109]. Software now implements the technology independently from hardware, and it is not limited by hardware architecture any longer [50]. These capabilities are usually found in hardware, such as network access, services, and applications. By utilizing standard servers instead of custom devices, NFV provides network functionality. The NFV-enabled SDVN improves service provisioning, flexibility, service delivery, and reliability. An SDVN can be effectively used to deploy advanced applications, such as NFV.

*Software-Defined Heterogeneous Vehicular Networks*: Due to heavy data traffic [41,110], it is difficult to have load balancing among vehicles and RSUs in SDN. Therefore, integrating SDN and HetVNET (called a software-defined heterogeneous vehicular network (SDHVN)) balances the load and provides cooperative data dissemination between vehicles and RSUs [67]. A centralized service architecture enhances the distribution of data in SDHVN environments, as shown in Figure 6. The SDHVN makes transport networks coordinated and safer [111]. Moreover, it plays a significant role in managing network services and providing reliable communication [47]. Vehicle users benefit from the SDHVN's wide coverage and high throughput through the use of cellular networks. A Virtual Network Function (VNF) allows flexible resource scheduling in an SDHVN.

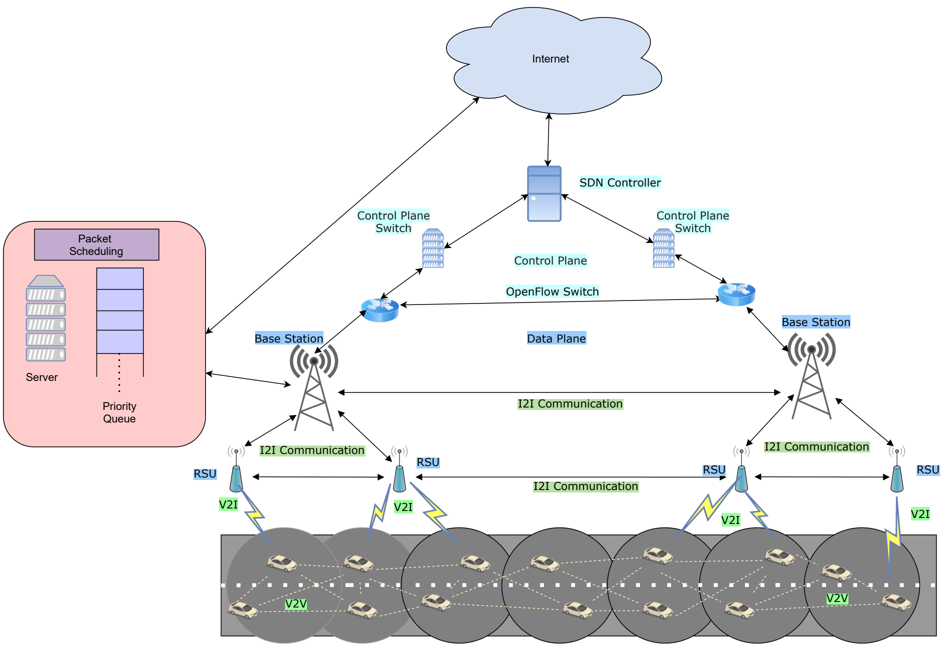


**Figure 6.** The general architecture for iSDHVN [112].

*Packet Scheduling*: Packet scheduling ensures that packets are transmitted efficiently and fairly across the network while meeting different applications' quality-of-service (QoS) requirements. Packet scheduling becomes more challenging in certain scenarios, such as networks with high traffic loads, heterogeneous traffic, or real-time applications requiring low latency and high reliability [113]. In these scenarios, packet scheduling must be designed to prioritize traffic based on the QoS requirements of different applications and to handle congestion and network fluctuations to maintain the desired level of service. Another challenge with packet scheduling is the limited resources available to the scheduler, such as buffer space, processing power, and memory. As the number of packets and applications increases, the scheduler must use the available resources efficiently to avoid delays and congestion [114].

The type of scheduler used can also affect the performance of packet scheduling. Different scheduling algorithms have different trade-offs between fairness, throughput, and delay, and the choice of the scheduler can significantly impact network performance [56]. Packet scheduling is a general task in any network, but its challenge varies depending on the specific context. The challenge with packet scheduling is to ensure that packets are transmitted efficiently and fairly across the network while meeting the QoS requirements of different applications. Due to the high-speed movement of vehicles on highways, network connectivity changes frequently, and it is a challenging task for multi-hop data dissemination in VANETs [115]. Thus, packets cannot reach the destination within the period [116]. Hence, the packet flow is disturbed, resulting in high latency and routing overhead. Thus, a packet-scheduling strategy through queueing models provides the solution, where each packet transmission is scheduled to maximize the packet delivery ratio, avoid time slot allocation issues, improve packet delivery, and decrease latency. Packet scheduling also improves the QoS in the VANET with the help of SDN [117].

*Network Utility Maximization (NUM)*: NUM is used to monitor the efficient usage of network resources in wireless networks [118]. In vehicular networks, it can be used to monitor different parameters, which include traffic distribution, route selection, packet delivery, latency, and so on. NUM can be formulated as a node-based optimization problem for improving various performance metrics in the network [119]. The fairness of networks at runtime can be achieved by finding the optimal values in the queueing theory, which dynamically tends to achieve fairness [120]. This will further lead to longer network connectivity in VANETs.

### *4.2. Software-Defined Internet of Vehicles*

SDIoV technology has been identified in association with different issues in this survey. The Software-Defined Internet of Vehicles (SDIoVs) is an emerging architecture that integrates SDN and the Internet of Vehicles (IoV) to enable ITSs [121,122]. SDIoV uses SDN to provide centralized control of the IoV, which enables efficient communication, management, and coordination of vehicular networks [123]. The SDN controller in an SDIoV system can dynamically manage network resources and traffic, allowing vehicles to efficiently communicate with each other and with the infrastructure [124,125]. This allows for the real-time coordination of traffic and intelligent routing decisions, which can improve traffic flow and reduce congestion. SDIoV also provides a platform for deploying a wide range of ITSs, such as collision avoidance, automated parking, and smart traffic lights [126]. By enabling more efficient communication and data sharing among vehicles and infrastructure, SDIoV can improve the efficiency, safety, and sustainability of transportation systems [61].

The use of SDN in IoV environments also addresses some of the challenges associated with traditional IoV networks, such as high mobility and network scalability [127]. By centralizing network control and management, SDIoV can reduce the complexity of network management and also enable the more efficient use of network resources. However, the implementation of SDIoV also presents some challenges, such as the need for reliable wireless communication and security mechanisms to protect against cyber-attacks [53]. Additionally, the deployment of SDIoV requires a significant investment in infrastructure, including sensors, communication devices, and other network components. SDIoV is an emerging architecture that integrates SDN and IoV to enable an ITS [69]. SDIoV uses SDN to provide the centralized control of vehicular networks, enabling efficient communication, management, and traffic coordination. SDIoV can improve transportation systems' safety, efficiency, and sustainability but also presents some challenges, such as the need for reliable wireless communication and security mechanisms.

### 4.3. Intelligent Digital Twin with SDVN

The taxonomy of conventional and recent advances in IDTSDVN applications refers to the taxonomy of these applications based on their characteristics and features. In terms of taxonomy, conventional IDTSDVN applications are typically focused in traditional areas such as healthcare, manufacturing, and transportation. Recent advances in IDTSDVN have expanded to areas such as smart cities, fog/edge computing [128], and IoT [129]. These applications can be further classified based on factors such as their goals, functions, and technologies used.

In terms of organization, a survey on IDTSDVN applications typically begins with an introduction that provides an overview of the topic and its importance. The survey then presents background information on IDTSDVN, including its definition, architecture, and components. The main body of the survey is then organized into sections or chapters that cover specific IDTSDVN applications and their characteristics, features, and implementation. The survey may also discuss the challenges and future directions of IDTSDVN applications. Finally, the survey concludes with a summary of the main findings and a discussion of the implications of the research for the field of IDTSDVN. As illustrated in Figure 7, IDT-SDVN consists of two key components: the real-world SDVN and its intelligent digital virtual counterpart [62]. The physical SDVN is a network that operates in the real world. Whenever a controller is configured as a mobile edge computing (MEC) server, routing requests are computed and vehicles are scheduled [70]. As for the controller, it represents and validates the immediately learned functional model as a virtual network (or networks). The revised routing schemes are examined in virtual networks, and the best-performing scheme is chosen to be installed in the physical network [72].

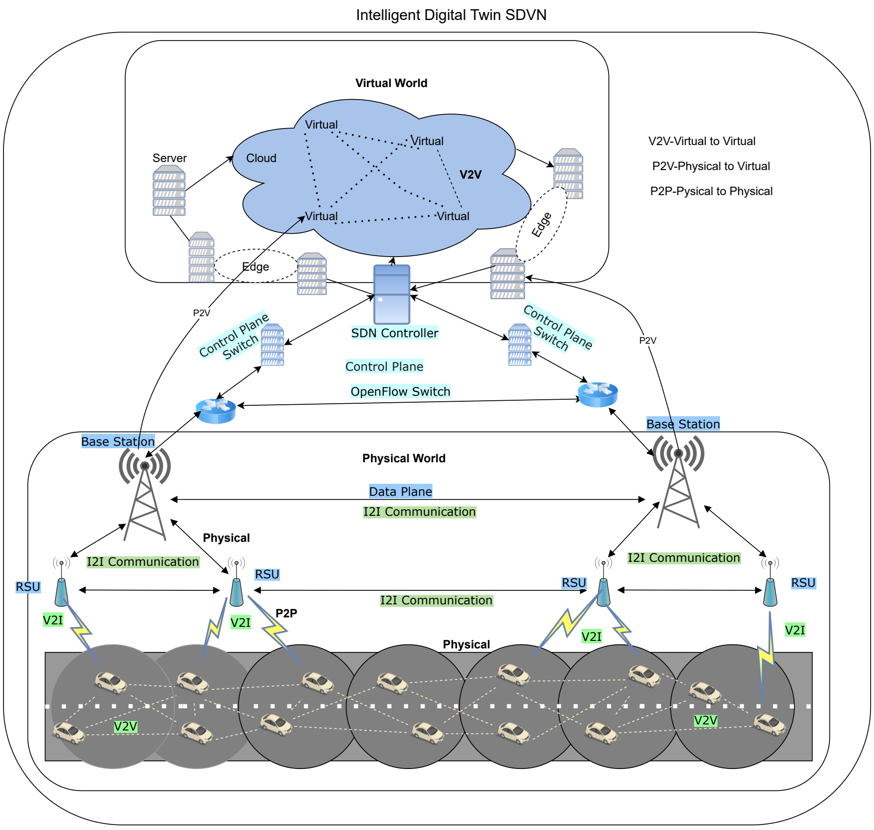


**Figure 7.** Architecture for intelligent digital twin SDVN [62,70,72,73].

In the case of the Policy-Based IDT-SDVN (shown in Figure 8), the controller periodically communicates the routing policy to each vehicle. Except for the computation of flow tables, the routing policy refers to all sorts of rule-related information. Whenever routing metrics are updated, routing protocols are switched, or other intelligence rules are implemented, and these rules can be locally agreed upon. In addition, routing policies can be adjusted regularly, based on findings for virtual networks from existing works [73]. In the Routing-Based IDT-SDVN, the routing table is mainly determined in the controller. Intelligent algorithms also promise to compute routes with the least amount of overhead on the network [62]. It is possible to construct the flow table predictably using temporal routing and the Markov model, for instance. Additionally, IDT can use other algorithms, such as reinforcement learning, to improve routing schemes based on vehicle availability in dynamic networks where routing methods are based on the vehicle's location information [65].

1. *Edge Layer*: In the context of intelligent digital twin networks, the edge layer refers to the layer of computing devices and sensors that are located close to the physical systems being monitored and controlled. These edge devices are capable of collecting and processing data from sensors. They can also run local analytics and decision-making algorithms and communicate with other edge devices or higher-level cloud-based systems [130].
   One of the key advantages of using edge computing in intelligent digital twin networks is the ability to process data closer to their source, reducing latency and enabling real-time decision making. This is particularly important in applications such as industrial automation, visualizing high-quality 3D contents [131], or autonomous vehicles, where even small delays in processing and decision making can have significant consequences. Additionally, edge computing can help to reduce data communications with cloud-based systems, which can help to reduce network congestion and lower costs. By performing the local processing and filtering of data, edge devices can send only the most important information to higher-level systems for further analysis and decision making [132]. Overall, the edge layer is important in enabling the efficient and effective operation of intelligent digital twin networks, particularly in applications where real-time decision making is critical, as shown in Figure 8.
2. *Communications*: Reliability refers to the ability of the network to deliver data without loss or errors. High reliability is critical for applications that require constant and accurate data delivery, such as real-time control systems or medical applications [133]. Latency is the time delay between the transmission of data and their arrival at the destination. Video conferencing or online gaming, which require real-time responses, depend on low latency. During a given period, a network's capacity is how much data it can transmit. High capacity is critical for applications that require large data transfers, such as video streaming or file sharing. Connectivity refers to the ability of a network to connect devices and enable communication between them. Good connectivity enables communication between devices and provides a seamless user experience. These metrics are often considered to estimate communication networks' QoS and design new networks that meet the requirements of specific applications.
3. *Internet of Things*: A network can be segmented into multiple virtual networks by using network slicing, each with its own characteristics and set of resources [134]. This allows for the creation of customized network environments to meet specific application requirements, such as low latency or high bandwidth. Network optimization is the process of improving the performance of a network by maximizing its efficiency and minimizing its latency, congestion, and packet loss. This can be accomplished through various techniques, including traffic engineering, load balancing, and resource allocation. Routing is the process of selecting the best path for data to travel across a network from a source to a destination. This involves determining the most efficient route based on factors such as distance, traffic congestion, and network

topology [135]. Various routing protocols, such as OSPF (Open Shortest Path First) and BGP (Border Gateway Protocol), are used to accomplish this.

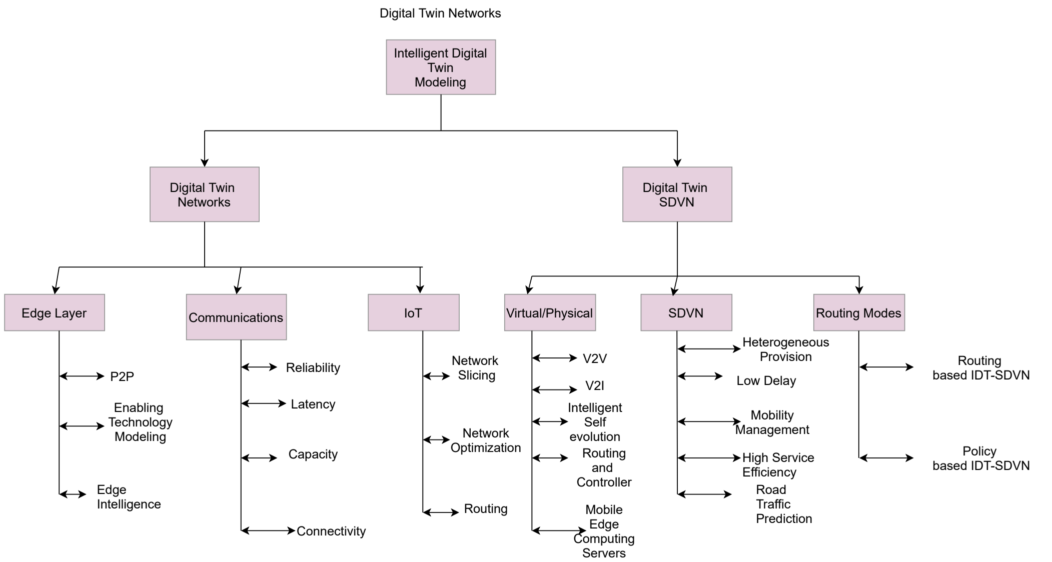


**Figure 8.** The taxonomy of conventional and recent advances in IDTSDVN applications and the organization of this survey.

Digital twin SDVN is an emerging concept that combines digital twin and SDN technologies to extend the performance of the vehicular network [136]. In this way, network management can be more efficient. Digital twin SDVN refers to the creation of a virtual representation of a vehicular network, known as a digital twin, and its integration with the physical network. Digital twins provide a real-time view of the physical network, collecting and analyzing data to provide insights into traffic patterns, network performance, and other metrics [137]. This information is then used to optimize network operations and improve the overall user experience. SDN technology manages the digital twin and the underlying physical network, providing centralized control and programmability. This enables the network operator to allocate resources dynamically, reroute traffic, and adjust network configurations as needed to optimize network performance and meet changing user demands. Digital twin SDVN can be used to support a wide range of vehicular applications, including connected vehicles, ITS, and autonomous driving. By providing real-time insight into network performance and enabling dynamic network management, it can help to improve safety, reduce congestion, and enhance the overall efficiency of vehicular networks.

## 5. Performance Evaluation of iSDVN

Considering that vehicles are so crucial in the IoT, VNs have been extensively researched for their ability to facilitate efficient connectivity between vehicles and infrastructures for a variety of applications. The Internet of Vehicles (IoV) is a component of the IoT [66,71]. Unlike other sorts of mobile devices and networks, automobiles move dynamically within road networks. In the last two decades, VANETs have been investigated as a way to connect cars in large regions with multi-hop communication. Nevertheless, VANETs will eventually contribute to next-generation VNs due to their multi-hop and self-organizing capabilities, enabling the network to extend its coverage [94]. Consequently, VNs are referred to as VANETs throughout this survey.

As a solution to the above, the iSDVN has emerged as a promising architecture in recent years for ITSs, as shown in Figure 5, with the current study demonstrating that it can reduce latency and packet drops while taking into account software-defined network characteristics such as decoupling networking and data forwarding. The controller will give far more powerful processing capability than individual vehicles in such a network architecture. In this context, the intelligent digital twin based on the SDVN reduces the cost of networking equipment, allowing clever schemes for smart vehicles and IoV to be realized [62].

### *5.1. Challenges of Multi-Service Provisioning of QoS for iSDVN and iSDHVN*

Multi-service provisioning refers to the ability of a network to support the delivery of multiple types of services, such as voice, video, and data, over a single infrastructure. With the increasing demand for new services, the ability to deliver multiple services efficiently and cost-effectively has become essential for network operators. Typically, it is achieved through the use of QoS mechanisms that ensure that different types of traffic are prioritized in accordance with their requirements. QoS mechanisms can help ensure that the network resources are used effectively, and the delivery of critical services is not compromised.

In addition to QoS mechanisms, network operators can also use Service Level Agreements (SLAs) to guarantee service quality for specific applications or customers. SLAs can include specific requirements such as bandwidth, latency, and packet loss rates and can help ensure that critical services are delivered with the desired level of performance. Multi-service provisioning can be challenging for network operators, as different services may have different requirements for bandwidth, latency, and other metrics. This requires careful planning and management to ensure that the network is optimized for the delivery of multiple services. It is typically achieved through the use of QoS mechanisms and SLAs, which prioritize different types of traffic based on their requirements and guarantee service quality for specific applications or customers. Effective multi-service provisioning requires careful planning and management to optimize the network for the delivery of multiple services.

The aim of this work was to improve the reliability of service provisioning in iSDVNs. We examined how SDN has evolved into new wired and wireless networking applications and end-user services. Multiple wireless network technologies are integrated into SDN to support and improve QoS. The iSDVN enables link reliability in V2V environments, especially in an SDVN controlled by a centralized server. To improve vehicular safety, queueing-based models are most appropriate for evaluating SDN controllers and switches. The utilization of resources, traffic flow, and queue management are optimized. As data traffic flows or services are provisioned, network management becomes feasible. The logically centralized management of an SDVN allows V2V communications to be conducted efficiently. In the control plane, high-priority messages can be sent through wired or wireless channels allocated to specific controllers and switches.

A queueing-based model is found to be more effective for evaluating controllers and switches. The iSDVN system has been designed to balance high traffic loads and data services. A packet flow's service time is based on an exponential distribution in iSDVNs. In the queueing-based model, a path selection approach is used, queues are modeled with the controller, and traffic flow is controlled by switches. VNC (virtual network customization) can be increased with SDN. For using multi-service provisioning in an SDVN, we propose the multi-hop cooperative data dissemination approach to enhance data link reliability and stability and select the best route for packets from the source to the destination. Data traffic load balancing in vehicular networks is a significant problem that SDN heterogeneous vehicular networks can handle [138]. To minimize network management latency and maximize network utility, the iSDHVN controller controls events over the cellular network. Throughput and resource utilization are optimized with the proposed enhanced service reliability model, which also reduces resource consumption and minimizes response time.

### 5.2. Techniques Analyzed in iSDVN

This section describes the challenges identified since the survey started in wireless networks, VANETs, HetVNETs, iSDVNs, and iSDHVNs. In Section 2, we examine data dissemination, data forwarding, latency, and load-balancing issues associated with SDVN networks, as well as network connectivity, network congestion, routing, scheduling, and mobility. Hence, examining the hierarchical environment in VANETs, SDVNs, and iSDHVNs and the merits and demerits associated with them is necessary. Statistically analyzing the networks' performance indicators and explaining why stochastic models are used to solve workload problems in SDVNs is also presented by Zhao et al. [78]. In order to assess the performance of SDVNs and iSDVN systems, various parameters need to be considered, such as random traffic flow and data dissemination schemes, cooperative scheduling, and load-balancing algorithms for queueing networks [19,31]. As a result of a small collection of resources in routing and scheduling algorithms, traffic flow mobility and server resource usage are generally reduced. As a result of SDN, organizations can access a heterogeneous collection of services, scale, ensure reliability, stay consistent, be flexible, and programmable. The network performance in iSDVN and iSDHVN has been analyzed and modeled using stochastic models.

### 5.3. Integration of SDN with Other Technologies

The integration of SDN with other emerging technologies is an important trend in the development of vehicular networks. The integration of SDN with other technologies can enable new services, enhance network performance, and improve the overall efficiency of vehicular networks. One technology that can be integrated with SDN is edge computing. Essentially, edge computing is meant to bring computation and data storage closer to the data generation edge of a network. By integrating edge computing with SDN, it is possible to reduce the latency and improve the response time of vehicular applications. For example, the combination of edge computing and SDN can enable intelligent decision making by analyzing data in real time at the edge of the network.

Another technology that can be integrated with SDN is artificial intelligence (AI). AI can be used to enhance the intelligence of vehicular networks by analyzing and learning from data collected by the network. By integrating AI with SDN, it is possible to develop more efficient and intelligent routing algorithms and to optimize network resources for better performance. The integration of 5G with SDN is also a promising trend. Offering high-speed connectivity and low latency, 5G is the next generation of wireless communication technology. By integrating 5G with SDN, it is possible to provide reliable and efficient communication for vehicular networks. SDN can be used to optimize the use of 5G resources and to enable more efficient traffic management and routing.

Finally, integrating Blockchain technology with SDN can provide additional security and privacy for vehicular networks. Blockchain can be used to create a tamper-proof ledger of all the transactions that occur in the network, which can help prevent malicious attacks and ensure users' privacy [139]. Integrating SDN with other emerging technologies, such as edge computing, AI, 5G, and Blockchain, can enhance vehicular networks' intelligence, performance, and security. This integration is an important trend that is driving the development of next-generation vehicular networks.

*SDN in VANETs*: Stochastic network optimization and SDVNs are presented in this section to improve packet forwarding. The source and destination nodes of VANETs operate on a queueing model. VANETs are quickly becoming SDN networks with the help of new technologies. The IEEE 802.11p/1609 vehicular communication protocol provides efficient data transmission to VANETs [140]. The integration of this technology allows us to monitor vehicles, which improves traffic management and makes transportation more efficient. Various studies have been conducted on VANETs in terms of their efficiency in disseminating data. As SDN changes, the VANET topology can be adjusted. A VANET's control plane is decoupled from its assimilation and network management support. As part of these services, network infrastructure virtualization is proposed in [41]. In [42], an architecture for a hierarchical SDVN is proposed. As a result of packet loss and poor connectivity, a communication protocol was developed to address it through the controller [63]. In [37], the authors abstracted heterogeneous wireless devices such as vehicles and RSUs to achieve rapid network innovation. The benefit of logically centralized control planes is that they provide better configuration capabilities by improving the quality of service.

The location of vehicles, traffic flows, and the cooperative data scheduling of vehicles have been studied [3]. V2I communication is enabled by RSUs picking up data from source and destination vehicles. SDN-enabled vehicular networks are managed and resource-utilized efficiently by their controllers. Wireless communication technologies are often integrated with SDN paradigms to support vehicular communications [49]. The SDVN routing protocol takes performance metrics into account, resulting in stable routes and the shortest communication delays [8,58]. Consequently, packet delivery is improved, and packet flow setup delay is reduced. Data from the RSU cloud can be disseminated across the network using the SDN controller. By determining the shortest path and most stable route between communication nodes, this model minimizes the optimal delay in the network.

SDN switches are analyzed based on several key factors, including the packet arrival rate, service rate, and waiting time [40]. Next-generation networks have a faster data transmission rate than 4G networks [46]. Network packet loss is caused by dynamic topologies due to their short lifetime links. Dynamically optimized VNC data transfer and service performance were implemented to meet vehicle specifications. Due to the highly dynamic mobility of vehicles, reconfiguration delays can be higher in vehicular networks. To ensure a short recovery time and reasonable packet delivery rates, an SDN controller simulation is utilized to evaluate this architecture. SDN controller performance was modeled and predicted using a wireless network virtualization model in [39,43]. To maximize reliability and minimize delay, this model was analyzed. Accordingly, the proposed model maximized reliability in SDN-based vehicular networks based on arrival and service rates compared to the analysis in [141].

When communicating packets, OpenFlow switches to reduce maximum load balancing. Data-plane and control-plane traffic flows can also be implemented using queueing theory. The queueing model minimizes latency problems caused by the dense flow of packets. Using OpenFlow controllers and switches also optimizes data traffic forwarding [142]. Controllers and switches deliver the data plane of SD-VANET systems. The authors of [39,46,59,143] have not considered the control of event decisions. Using the multi-server queue technique, SDVN maximizes reliability, minimizes controller response time, and enhances packet flow rules. Compared to existing work, the proposed work shows SDVN's reliability and service level agreement, which are shown in Table 2.

**Table 2.** Performance metrics considered in SDVN by most of the researchers.

| Work Conducted | Reliability | Utilization | Delay | Multi-hop | SDVN | Mobility | Throughput | Flow Rule | Digital Twin |
|---|---|---|---|---|---|---|---|---|---|
| He et al. [37] | ✗ | ✓ | ✗ | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ |
| Ravi et al. [3] | ✓ | ✗ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ |
| ravi et al. [11] | ✗ | ✗ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ |
| Sood et al. [40] | ✗ | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ | ✓ | ✗ |
| Liyanage et al. [46] | ✗ | ✗ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ |
| ravi et al. [96] | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✓ | ✗ |
| Xiong et al. [39] | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Thiruvasagam et al. [141] | ✓ | ✗ | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Halabian et al. [142] | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Misra et al. [59] | ✗ | ✗ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ |

*SDN in Heterogeneous Vehicular Ad Hoc Networks*: The purpose of this section is to present an approach to multi-hop cooperative data dissemination in SDHVNs that improves the forwarding of data traffic, the utility of the network, and the reliability of the network. Through the data plane, the SDHVN transmits and receives packets. One of the new emerging technologies in VANETs is SDN, enabling vehicle monitoring. The SDN architecture in VANETs is attracting more research attention. The authors of [37] propose an SDN-based approach for heterogeneous vehicular communications to enable rapid network innovation. Our research has focused on optimizing VANET latency and delay control. It has been proposed to use time constraints to schedule heterogeneous vehicular networks using SDN. LTE-integrated V2V and V2I communications are enabled by IEEE 802.11p/1609. A hybrid V2I/V2V packet-scheduling algorithm enhances cooperative data dissemination in an SDVN [144].

In the control plane, a 5G-enabled SDVN, packet-scheduling algorithms, and SDN architecture were applied for data forwarding to the data plane. Although the authors examined general issues associated with heterogeneous vehicular systems, they do not have a specific solution. Routing and scheduling requirements for data communication in VANETs take into account a variety of network resources. SDN controllers control packet schedulers for heterogeneous vehicular networks [38]. As described in [54], the authors proposed an integrated hierarchical architecture for the IoV, which can enhance the reliability and scalability of data services. Data trafficking and network management have become more flexible, which makes future ITSs possible. The SDVN framework facilitates data dissemination in an efficient and effective manner. The controller in VANETs controls high mobility and multi-hop paths to achieve high reliability and throughput. A dynamic vehicular connection management approach was developed by the authors to guarantee the quality of service in an SDIoV. The authors of [58] investigated various factors related to link stability to optimize routes for packet delivery. The SDN controllers improve packet delivery and decrease latency by managing traffic flow cooperation and network availability.

To maximize network utility, SDVN and dynamic stochastic network optimization are studied. Furthermore, the sharing of information at the mobile edge of a SD 5G VANET is emphasized, as well as the improvement of latency and reliability. The utilization of resources and the quality of service that VANETs provide must be balanced. Due to the different QoS requirements for multi-class services, the SDHVN prioritizes different functions and ensures fairness. Vehicle networks place a high priority on safety-related services. An innovative packet-scheduling approach is proposed for resource management in VANETs [145]. SDHVN's data dissemination utility is enhanced by it, as well as the multi-class QoS performance. According to He et al. [37], VANET data dissemination poses the largest problem. This scheme enhanced QoS over the available existing models in studies performed by Gong et al. [45], Dai et al. [51], and Chal et al. [57]. Due to the fact that most SDHVNs are cooperative, a novel multi-hop cooperative data dissemination system with packet scheduling can be envisioned for SDHVNs.

*SDN in Internet of Vehicles*: This section integrates the SDN concept with IoV, demonstrating its excellent benefits [146]. The control plane controls data forwarding and flow-table matching. An SDN controller can, however, make better routing decisions based on a global view of the network topology. Table 3 presents a comparison of related work on SDN-based IoV [147]. Centralized/distributed SDN architectures were compared for most work-related tasks. With SD-IoV, latency control is reduced by using the higher mobility of vehicles in SD-VANET systems and the additional link/disconnection that occurs in SD-VANET systems [44].

*Digital Twin Integrated with SDN*: Digital twin technology integrated with SDN can enhance network management in several ways.

Data ingestion in the digital twin allows for the real-time monitoring and visualization of network elements, flows, and traffic patterns. To make informed decisions, administrators can visualize and analyze the current state of the network. The digital twin can predict potential network issues or performance bottlenecks based on historical data and network behavior patterns. As a result, administrators can take proactive measures before problems worsen. With the digital twin, administrators can optimize resource allocation, traffic engineering, and load balancing in real time, thus enhancing the efficiency of their networks. When network faults occur, the digital twin can act as a sandbox for conducting virtual experiments to identify the root cause and test potential solutions before implementing them in real time.

*Intelligent Digital Twin for SDVN*: The research on intelligent DTs for SDVNs can be novel and cutting-edge. SDVN technology combined with DT technology offers opportunities for innovation and advancement in vehicular networks. The following aspects can contribute to the novelty of such work: In order to develop an intelligent digital twin, artificial intelligence (AI) techniques are integrated with the SDVN. As a result of this fusion, the digital twin can learn from real-time network data, make predictions, and adjust its configurations and policies automatically as conditions change. It is a novel approach to managing vehicular networks that can revolutionize the field by combining AI and SDVN. Using AI-driven optimization techniques, DTs can efficiently allocate resources to support various vehicular services, such as infotainment, traffic management, and vehicle-to-vehicle communication. This capability allows SDVN applications to be met with a novel and intelligent approach. The intelligent digital twin uses machine-learning algorithms to detect anomalies and identify abnormal network behavior. A novel contribution to SDVN research is the ability to enhance network security and resilience through this capability. In addition to vehicle sensors, communication devices, and infrastructure, the intelligent digital twin can gather data from many sources. Research on SDVNs focuses on integrating and analyzing heterogeneous data for intelligent decision making.

**Table 3.** Performance metrics of E2E delay bound analysis in iSD-IoVs.

| Work Conducted | Architecture | Contribution | Method | Delay Bounds | Digital Twin |
|---|---|---|---|---|---|
| Deng et al. [44] | Centralized | SD-IoV | Optimization | ✗ | ✗ |
| Bilen et al. [148] | Centralized | SDUDN | Queueing model | ✓ | ✓ |
| Sood et al. [40] | Centralized | CPU Utilization | Queueing Model | ✓ | ✗ |
| ravi et al. [96] | Centralized | Packet Scheduling | Queueing Model | ✓ | ✗ |
| Mahmood et al. [149] | Centralized | SDN-based VANETs | QoS Resources | ✗ | ✗ |
| ravi et al. [3] | Centralized | Data Scheduling | Queueing Model | ✓ | ✗ |
| Liyanage et al. [46] | Hierarchical | SDVN | CPP | ✓ | ✗ |
| kumar et al. [150] | Heterogeneous | SD5GNet | Queueing Model | ✓ | ✗ |
| Ye et al. [151] | Heterogeneous | VNF-5G core networks | Queueing Model | ✓ | ✗ |

## 6. Open Issues

Several approaches are described in the literature; however, there are still many gaps and challenges in SDVNs. One approach that has shown promise in addressing these challenges is the use of intelligent digital-twin-based SDVNs. The intelligent digital-twin-based SDVN is a promising approach to addressing the challenges and gaps in SDVNs, as shown in Figure 9. Software-defined networking (SDN) and digital twin technology can be integrated to enhance network management, optimization, and decision making. In order to fully realize the potential of SDN through the use of digital twin technology, some open issues and challenges have to be addressed. The following paragraphs describe some open issues.

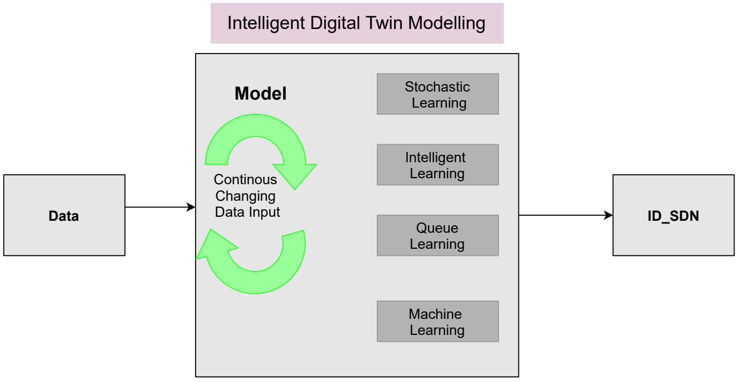


**Figure 9.** The scope of intelligent digital-twin-based SDVN [73].

### 6.1. Controller Placement Problem

The controller placement problem is crucial in minimizing delay in SDN-based VANETs. By installing local controllers in ideal locations and distributing the workload, individual controllers can handle the traffic efficiently. Using queueing models, delays over wired and wireless links can be assessed and minimized while controllers are located. In order to describe the finite queue of each vehicle OBU and RSU, the packet arrival rates follow a Poisson distribution with a mean packet arrival rate. The controller placement problem in an SDVN is complicated by various factors, and the trade-off between the controller number and latency is one of them. If too few controllers are used, the delay experienced by OBUs located far away from the controllers may increase, which is undesirable in delay-sensitive VANET applications. At the same time, deploying too many controllers may increase the overhead and result in increased latency due to the communication delay among the controllers.

### 6.2. Resource Allocations

Each vehicle is equipped with computing resources, such as computing power, storage, and so on [152]. The SDVN with inter-vehicular communication is an emerging technology for effective safety and entertainment information distribution. However, due to fast mobility and variable vehicle density, highly dynamic VANET topology might produce unstable wireless connections, resulting in more significant packet loss and increased transmission latency, posing problems in ensuring the QoS [153]. DV2I and V2V communications can both be enabled by Dedicated Short-Range Communications (DSRC).

There have been a slew of new services fueled by mobile devices and the exponential growth of mobile internet traffic, including computation-intensive, content-centric, and delay-sensitive services [154]. To maximize VANET speed, it is vital to allocate networking, caching, and computing resources. Spectrum/bandwidth, power, and time slots are some of the radio resources that can be managed in vehicular communication [155]. As a result, the allocation and management of resources are challenging to resolve and differ significantly from one another.

### 6.3. Mobility Control

The increasing mobility of vehicles in the context of SDVNs presents significant challenges for network stability and management. As vehicles move at high speeds and change their locations frequently, the wireless channels used by an SDVN become unstable, leading to data transmission errors and delays. This can result in difficulties in acquiring real-time data from the vehicles and networks using the controller, leading to delays in the controller's command distribution. To address this challenge, various solutions have been proposed, such as the use of predictive algorithms and mobility-aware routing protocols. However, these solutions are still in their infancy and cannot be fully implemented in SDVNs.

One potential solution to the high-mobility challenge is the incorporation of vehicle movement behavior in network stability prediction. By predicting the movement of vehicles in a given network environment, it may be possible to anticipate wireless channel instability and take proactive measures to prevent data transmission errors and delays. However, incorporating vehicle movement behavior into network stability prediction is a complex and challenging task. It requires the use of sophisticated algorithms that can accurately model and predict the movement of vehicles in a given network environment. Additionally, it requires the integration of data from multiple sources, such as vehicle sensors, network infrastructure, and historical data, to create an accurate predictive model. Despite the challenges, efforts are being made to develop predictive algorithms that can accurately model and predict the movement of vehicles in high-mobility environments. These efforts hold promise for enabling the more effective control and management of SDVNs in high-mobility scenarios, improving their overall performance and reliability.

### *6.4. End-to-End Delay*

In SDVNs, the number of controllers utilized can have a significant impact on the end-to-end delay experienced by OBUs (On-Board Units) in the network. If only a few controllers are used, OBUs that are far away from the controlling RSUs (Road-Side Units) may experience significant route setup delays. This is because the controllers need to communicate with the RSUs and other controllers to establish routes, which can lead to long delays for OBUs that are farther away from the controllers. Delay-sensitive VANET applications require a minimal end-to-end delay to function correctly, so it is crucial to minimize the delay experienced by OBUs during the deployment of controllers. It is important to note, however, that latency is a trade-off between the number of controllers and the number of processors. OBUs can be improved by increasing the number of controllers, but the overhead and complexity of the network may also increase.

To address this trade-off, network designers need to carefully consider the number and placement of controllers in the network. They must balance the need for minimal end-to-end delay with the need to reduce the overhead and complexity of the network. One approach is to use distributed control, where the control plane is distributed across multiple controllers, each responsible for a specific area of the network. This approach can help minimize the delay experienced by OBUs while reducing the overhead and complexity of the network. In summary, the number and placement of controllers in SDVNs can have a significant impact on the end-to-end delay experienced by OBUs. In designing SDVNs, it is important to consider the trade-off between a number of controllers and latency, as well as the need to reduce overhead and complexity while maintaining minimal end-to-end delay. Distributed control can be an effective approach for minimizing delay while reducing network overhead and complexity.

### *6.5. Quality of Service (QoS)*

While early versions of SDN and OpenFlow may not have explicitly supported differentiated QoS, recent developments have been made to incorporate QoS mechanisms into SDN networks. For example, the OpenFlow 1.3 specification includes support for QoS and traffic classification, allowing for the creation of virtual networks with different QoS requirements. Additionally, SDN controllers can implement QoS policies and traffic-engineering strategies to ensure that different types of traffic are handled appropriately. In order to enable end-to-end QoS signaling across distributed SDN domains, session control protocols can be used as a northbound interface. Using this approach, multiple applications can be managed in real time with flexible and differentiated QoS provisioning. The configuration of many QoS mechanisms currently requires human intervention, impairing network flexibility. In order to provide QoS support for SDN-enabled applications without using OpenFlow, approaches such as the OpenQoS framework have been developed, assisting network administrators in defining the QoS strategy that flows should adhere to and how the controller can allocate resources and differentiate services.

Ad hoc networks lack centralized management, which can lead to issues with congestion and prioritization of messages. This can be especially problematic in vehicular networks, where the large number of vehicles on the road and their constantly changing positions can result in a significant amount of network traffic [156]. However, there are solutions being developed to address these issues, such as using intelligent routing algorithms and prioritizing certain types of messages, such as emergency messages, to ensure timely and reliable delivery.

### 6.6. Stochastic Learning

Stochastic learning algorithms are a class of optimization algorithms that utilize random variables to optimize objective functions or identify the fixed points of functions that are only accessible through noisy observations. These algorithms are commonly used in reinforcement learning to improve the performance of networks, such as in the case of IDT SDVN. It is one of the most popular stochastic learning algorithms used in reinforcement learning. Using this method, agents learn the optimal Markov decision process policy to follow. The optimal policy can be determined by the fixed point of an expectation function, which is the optimal state–action value function. However, in the context of the SDVN, the optimal state–action value function is not directly accessible due to the complex and dynamic nature of the network environment. The network state may change rapidly due to various factors, such as traffic patterns, network topology, and network failures. This makes it challenging to accurately estimate the state–action value function for each state and action in the network.

To address this challenge, researchers have proposed several extensions of the Q-learning algorithm, such as the Deep Q-Network (DQN) algorithm, which uses deep neural networks to estimate the state–action value function [157]. The DQN algorithm has been shown to be effective in learning the optimal policy for complex and dynamic network environments, such as in the case of SDVNs. In summary, stochastic learning algorithms, such as the Q-learning algorithm, can be used to optimize network performance in IDT SDVN. However, the dynamic and noisy nature of the network environment requires modifications to these algorithms to make them effective in practice. Extensions of these algorithms, such as the DQN algorithm, have been proposed and shown to be effective in addressing the challenges of dynamic and noisy network environments.

### 6.7. Intelligent Networking

It is possible to improve routing metrics, protocol switching, adaptive routing, and load balancing using learning algorithms. As the controller learns from the collected data, he or she can construct networks according to the learned data. Recursive updating of networking schemes can be achieved by learning the physical world and the entire network, on the other hand.

Optimizing network resources involves maximizing their use. Intelligent networking intelligently shares and allocates frequency blocks among network traffic based on device signaling or control information [158]. Researchers have developed network scheduling models and used optimization for a wide range of scenarios. The typical strategy derives policy from a specific scenario. However, the practical network may encounter various complex environments that are vastly different from the scenarios discussed. Typically, the network's statistical properties are unknown, making optimization difficult. Distributed device randomness is a major issue for network scheduling. In this case, the network's communication and computation resources should be shared. Resources include communications and computations. Edges can communicate and offload data or computations to other edges or the cloud. In low-rate cases, they may reduce the processor frequency to save energy.

### 6.8. Queue Learning

In network-based systems, queueing theory is a well-established evaluation tool. This mathematical framework enables the evaluation of software-defined solutions and critical actors. By applying fundamental principles and analytical frameworks based on queueing theory, it can be applied to analyze network functionality. Queueing theory predicts the network's performance by analyzing the workloads associated with different traffic models. In recent years, researchers have paid attention to the application of queueing theory in SDN networks. This is because queueing theory provides a comprehensive and accurate model that can be used to address performance issues in SDN networks. By applying queueing theory in SDN networks, it is possible to improve network efficiency, reduce delays, and optimize resource utilization. This theory has been applied to extensive mathematical modeling, enabling researchers to evaluate different aspects of network performance, such as throughput, delay, and packet loss.

Furthermore, queueing theory can be used to evaluate different network topologies and configurations. It can be used to model the behavior of different SDN components, including switches, controllers, and applications, and analyze their impact on network performance. In summary, queueing theory is a valuable tool for evaluating the performance of SDN networks. Its comprehensive and accurate model can be used to optimize network efficiency, reduce delays, and improve resource utilization. By using queueing theory, researchers can evaluate different aspects of network performance and analyze the impact of different network topologies and configurations on network behavior [159].

### 6.9. Machine Learning

The mobility of vehicles, the dynamic spacing between vehicles, and the variable density of vehicles make it difficult to create and maintain end-to-end connections in a VANET. By predicting the moving patterns of vehicles, VANET performance can be improved for continuous service availability, and routing planning can be improved [160]. A SDN controller that uses artificial intelligence helps the VANET routing scheme predict mobility. The SDN controller utilizes advanced artificial neural networks to predict mobility accurately. Based on mobility prediction, the RSUs or the BS can estimate each vehicle's success probability and average delay when the network topology changes frequently. According to the estimation, vehicle arrival follows a Poisson process in a stochastic traffic model. Network systems need to be organized, managed, maintained, and optimized with more intelligence. Machine-learning techniques [55,161], however, are difficult to apply and deploy in traditional networks due to their inherently distributed nature. In SDN, we have the opportunity to provide network intelligence. An SDVN's capabilities (logically centralized control, global network view, software-based traffic analysis, and dynamic updating of forwarding rules) make machine-learning techniques more convenient to apply [162].

### 6.10. Zero-Touch Provisioning

Zero-Touch Provisioning (ZTP) in SDN (software-defined networking) is a process that automates the configuration of network devices, such as switches and routers, without requiring any manual intervention from network engineers. ZTP enables a more adaptive and agile network infrastructure, allowing network devices to configure themselves automatically based on the real-time changes in the network environment [3,64,163]. One of the primary advantages of ZTP in SDN is the reduction in human intervention, which can lead to faster decision making and fewer errors. With ZTP, network devices can be pre-configured with the necessary software and policies to function in a particular network environment [164]. Once connected to the network, these devices can automatically identify and adapt to changes in the network topology, traffic patterns, and other variables. This automated provisioning process can significantly reduce the time and effort required for network configuration, as well as eliminate the potential for human error that may occur during manual configuration. Additionally, ZTP can help ensure consistency across network devices, leading to better network performance and greater reliability. Overall, the use of ZTP in SDN provides several benefits, including increased agility, faster deployment, and reduced operational costs. By automating the configuration of network devices, ZTP allows network engineers to focus on more strategic tasks and frees up time and resources that would otherwise be spent on manual network configuration [87]. It also helps us when we have multiple vehicles. The manual configuration of multiple vehicles is hectic when humans are involved. So, automating configuration will add benefits to SDN to make it adaptable to the environment.

By addressing these open issues, digital twin technology will be integrated with SDN, allowing for more intelligent, adaptive, and efficient network management and control. In order to address these challenges and unlock the full potential of SDN, researchers and practitioners must collaborate to develop innovative solutions and best practices.

## 7. Conclusions

The survey on stochastic modeling in intelligent SDVNs has provided valuable insights into various aspects of software-defined vehicular networks. The findings highlight the challenges and opportunities in resource allocation, routing, scheduling, data dissemination, and performance analysis in VANETs and SDVNs. The survey emphasizes the impact of high mobility and dynamic network topology on resource allocation and response time in VANETs. It identifies the need for proper coordination and scheduling mechanisms to optimize data traffic flows and service provisioning in cooperative communication scenarios. A comparative study of VANETs and SDVNs highlights the importance of collision avoidance, data forwarding, connectivity, mobility, load balancing, and network utilization. It provides a comprehensive overview of existing techniques and solutions in SDN-oriented vehicular networks. However, the survey acknowledges the current limitations and challenges in implementing SDN in vehicular networks. The need for off-the-shelf SDN controllers and switches tailored to vehicular environments is a barrier to SDVN adoption. The survey calls for further research and innovation to address these challenges and develop mature solutions and protocols for SDVNs. In this survey, we point out the promising potential of incorporating digital twin technology into software-defined networking to enhance network management. SDVN infrastructures can be made more efficient and resilient because the digital twin delivers real-time insights, predictive analysis, and resource optimization. For SDVNs to fully take advantage of the benefits of digital twins, further research and experimentation will be necessary. In conclusion, this survey is a valuable resource for understanding the current state of stochastic modeling in intelligent SDVNs. It provides a foundation for future research and development in intelligent SDVNs. It also highlights the need for practical solutions and protocols tailored to vehicular networks' unique requirements.

**Author Contributions:** Conceptualization, B.R. and P.K.D.; data curation, C.K.D.; formal analysis, B.R., C.K.D. and S.N.S.; funding acquisition, P.K.D.; investigation, B.R. and S.N.S.; methodology, B.R., I.M., P.K.D., C.K.D. and S.N.S.; project administration, B.R.; resources, P.K.D.; software, I.M.; supervision, B.V., S.D. and S.N.S.; validation, B.R., B.V. and C.K.D.; visualization, B.R.; writing—original draft, B.R. and I.M.; writing—review and editing, B.V., P.K.D., S.D. and S.N.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work is partially supported by SERB, India, through grant CRG/2021/003888. We also thank financial support to UoH-IoE by MHRD, India (F11/9/2019-U3(A)).

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Not applicable

**Conflicts of Interest:** The authors declare no conflict of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| AODV | Ad Hoc On-Demand Distance Vector |
| BS | Base Station |
| CC | Cooperative Communications |
| CDF | Cumulative Distribution Function |
| CPP | Controller placement problem |
| DSRC | Dedicated Short-Range Communication |
| E2ED | End-to-end delay |
| eNodeB | Evolved Node B |
| eRELSERV | Enhanced reliability and service |
| HetVNET | Heterogeneous vehicular network |
| IDT | Intelligent digital twins |
| IoT | Internet of Things |
| IoV | Internet of Vehicles |
| IVC | Inter-vehicular communication |
| ITS | Intelligent Transportation System |
| LTE | Long-Term Evolution |
| MANET | Mobile ad hoc network |
| MDP | Markov decision process |
| MEC | Mobile edge computing |
| MHCDD | Multi-hop cooperative data dissemination |
| NFV | Network Function Virtualization |
| OBU | On-Board Unit |
| OSPF | Open Shortest Path First |
| P2P | Peer-to-Peer Networks |
| PDR | Packet delivery ratio |
| QoS | Quality of service |
| RSU | Road-Side Unit |
| RS-WLANs | Road-Side Wireless Local Area Networks |
| RU | Resource utilization |
| SCH | Service Channel |
| SDHVN | Software-defined heterogeneous vehicular network |
| SD-IoV | Software-Defined Internet of Vehicles |
| SDN | Software-defined networking |
| SD-VANET | Software-Defined Vehicular Ad Hoc Network |
| SDVN | Software-defined vehicular network |
| SLA | Service Level Agreement |
| SM | Stochastic modeling |
| SNC | Stochastic Network Calculus |
| V2I | Vehicle to Infrastructure |
| V2V | Vehicle to Vehicle |
| V2X | Vehicle to Everything |
| VANET | Vehicular ad hoc network |
| VAODV | Vehicular Ad Hoc On-Demand Distance Vector |
| VNF | Virtual Network Functioning |

## 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.
2. Al-Badarneh, 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.
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. [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 .

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. [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.
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.
8. Jiang, W. Software defined satellite networks: A survey. *Digit. Commun. Netw.* 2023, *in press*. [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*. [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. .: 10.1016/j.dcan.2021.10.004. [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.
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.
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. Mekki, T.; Jabri, I.; Rachedi, A.; Chaari, L. Software-defined networking in vehicular networks: A survey. *Trans. Emerg. Telecommun. Technol.* **2022**, *33*, e4265.
15. Monfared, S.K.; Shokrollahi, S. DARVAN: A fully decentralized anonymous and reliable routing for VANets. *Comput. Netw.* **2023**, *223*, 109561.
16. Islam, M.M.; Khan, M.T.R.; Saad, M.M.; Kim, D. Software-defined vehicular network (SDVN): A survey on architecture and routing. *J. Syst. Archit.* **2021**, *114*, 101961.
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.
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*.
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. [CrossRef]
20. Ameur, 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.
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.
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*.
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.
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*. [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.
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.
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.
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. Shahwani, H.; Shah, S.A.; Ashraf, M.; Akram, M.; Jeong, J.P.; Shin, J. A comprehensive survey on data dissemination in Vehicular Ad Hoc Networks. *Veh. Commun.* **2022**, *34*, 100420.
30. Chaudhary, P.; Gupta, B.B.; Chang, X.; Nedjah, N.; Chui, K.T. Enhancing big data security through integrating XSS scanner into fog nodes for SMEs gain. *Technol. Forecast. Soc. Chang.* **2021**, *168*, 120754.
31. Nahar, A.; Das, D. MetaLearn: Optimizing routing heuristics with a hybrid meta-learning approach in vehicular ad-hoc networks. *Ad Hoc Netw.* **2023**, *138*, 102996.
32. Yao, Y.; Shu, F.; Li, Z.; Cheng, X.; Wu, L. Secure Transmission Scheme Based on Joint Radar and Communication in Mobile Vehicular Networks. *IEEE Trans. Intell. Transp. Syst.* 2023, *early access*. [CrossRef]

33. 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.
34. 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.
35. Zhu, F.; Yi, X.; Abuadbba, 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*. [CrossRef]
36. Atallah, R.; Khabbaz, M.; Assi, C. Multihop V2I communications: A feasibility study, modeling, and performance analysis. *IEEE Trans. Veh. Technol.* **2016**, *66*, 2801–2810.
37. He, Z.; Cao, J.; Liu, X. SDVN: Enabling rapid network innovation for heterogeneous vehicular communication. *IEEE Netw.* **2016**, *30*, 10–15.
38. He, Z.; Zhang, D.; Liang, J. Cost-efficient sensory data transmission in heterogeneous software-defined vehicular networks. *IEEE Sensors J.* **2016**, *16*, 7342–7354. [CrossRef]
39. Xiong, B.; Yang, K.; Zhao, J.; Li, W.; Li, K. Performance evaluation of OpenFlow-based software-defined networks based on queueing model. *Comput. Netw.* **2016**, *102*, 172–185.
40. Sood, K.; Yu, S.; Xiang, Y. Performance analysis of software-defined network switch using $M/Geo/1$ model. *IEEE Commun. Lett.* **2016**, *20*, 2522–2525.
41. Yaqoob, I.; Ahmad, I.; Ahmed, E.; Gani, A.; Imran, M.; Guizani, N. Overcoming the key challenges to establishing vehicular communication: Is SDN the answer? *IEEE Commun. Mag.* **2017**, *55*, 128–134. [CrossRef]
42. Correia, S.; Boukerche, A.; Meneguette, R.I. An architecture for hierarchical software-defined vehicular networks. *IEEE Commun. Mag.* **2017**, *55*, 80–86. [CrossRef]
43. Zhang, N.; Yang, P.; Zhang, S.; Chen, D.; Zhuang, W.; Liang, B.; Shen, X.S. Software defined networking enabled wireless network virtualization: Challenges and solutions. *IEEE Netw.* **2017**, *31*, 42–49. [CrossRef]
44. Deng, D.J.; Lien, S.Y.; Lin, C.C.; Hung, S.C.; Chen, W.B. Latency control in software-defined mobile-edge vehicular networking. *IEEE Commun. Mag.* **2017**, *55*, 87–93. [CrossRef]
45. Gong, W.; Li, G.; Li, B. System utility based resource allocation for D2D multi-cast communication in software-defined cellular networks. *AEU-Int. J. Electron. Commun.* **2018**, *96*, 138–143. [CrossRef]
46. Liyanage, K.S.K.; Ma, M.; Chong, P.H.J. Controller placement optimization in hierarchical distributed software defined vehicular networks. *Comput. Netw.* **2018**, *135*, 226–239. [CrossRef]
47. Zekri, A.; Jia, W. Heterogeneous vehicular communications: A comprehensive study. *Ad Hoc Netw.* **2018**, *75*, 52–79. [CrossRef]
48. Ahmed, E.; Gha, H. Cooperative vehicular networking: A survey. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 996–1014. [CrossRef]
49. Peng, H.; Liang, L.; Shen, X.; Li, G.Y. Vehicular communications: A network layer perspective. *IEEE Trans. Veh. Technol.* **2018**, *68*, 1064–1078. [CrossRef]
50. Wang, K.; Yin, H.; Quan, W.; Min, G. Enabling collaborative edge computing for software defined vehicular networks. *IEEE Netw.* **2018**, *32*, 112–117. [CrossRef]
51. Dai, P.; Liu, K.; Wu, X.; Yu, Z.; Xing, H.; Lee, V.C.S. Cooperative Temporal Data Dissemination in SDN-Based Heterogeneous Vehicular Networks. *IEEE Internet Things J.* **2018**, *6*, 72–83. [CrossRef]
52. Luo, G.; Zhou, H.; Cheng, N.; Yuan, Q.; Li, J.; Yang, F.; Shen, X. Software-defined cooperative data sharing in edge computing assisted 5G-VANET. *IEEE Trans. Mob. Comp.* **2019**, *20*, 1212–1229. [CrossRef]
53. Mahmood, A.; Zhang, W.E.; Sheng, Q.Z. Software-defined heterogeneous vehicular networking: The architectural design and open challenges. *Future Internet* **2019**, *11*, 70. [CrossRef]
54. Liu, K.; Xu, X.; Chen, M.; Liu, B.; Wu, L.; Lee, V.C. A hierarchical architecture for the future internet of vehicles. *IEEE Commun. Mag.* **2019**, *57*, 41–47. [CrossRef]
55. Kumar, D.P.; Amgoth, T.; Annavarapu, C.S.R. Machine learning algorithms for wireless sensor networks: A survey. *Inf. Fusion* **2019**, *49*, 1–25. [CrossRef]
56. Din, S.; Paul, A.; Rehman, A. 5G-enabled Hierarchical architecture for software-defined intelligent transportation system. *Comput. Netw.* **2019**, *150*, 81–89. [CrossRef]
57. Chahal, M.; Harit, S. Network selection and data dissemination in heterogeneous software-defined vehicular network. *Comput. Netw.* **2019**, *161*, 32–44. [CrossRef]
58. Sudheera, K.L.K.; Ma, M.; Chong, P.H.J. Link stability based optimized routing framework for software defined vehicular networks. *IEEE Trans. Veh. Technol.* **2019**, *68*, 2934–2945. [CrossRef]
59. Misra, S.; Bera, S. Soft-VAN: Mobility-aware task offloading in software-defined vehicular network. *IEEE Trans. Veh. Technol.* **2019**, *69*, 2071–2078. [CrossRef]
60. Liu, K.; Xiao, K.; Dai, P.; Lee, V.C.; Guo, S.; Cao, J. Fog computing empowered data dissemination in software defined heterogeneous vanets. *IEEE Trans. Mob. Comput.* **2020**, *20*, 3181–3193. [CrossRef]
61. Hou, X.; Ren, Z.; Wang, J.; Cheng, W.; Ren, Y.; Chen, K.C.; Zhang, H. Reliable computation offloading for edge-computing-enabled software-defined IoV. *IEEE Internet Things J.* **2020**, *7*, 7097–7111. [CrossRef]
62. Zhao, L.; Han, G.; Li, Z.; Shu, L. Intelligent digital twin-based software-defined vehicular networks. *IEEE Net.* **2020**, *34*, 178–184. [CrossRef]

63. Aljeri, N.; Boukerche, A. Mobility management in 5G-enabled vehicular networks: Models, protocols, and classification. *ACM Comput. Surv. (CSUR)* **2020**, *53*, 1–35. [CrossRef]
64. Bonati, L.; D'Oro, S.; Bertizzolo, L.; Demirors, E.; Guan, Z.; Basagni, S.; Melodia, T. CellOS: Zero-touch softwarized open cellular networks. *Comput. Netw.* **2020**, *180*, 107380. [CrossRef]
65. Dai, Y.; Zhang, K.; Maharjan, S.; Zhang, Y. Deep Reinforcement Learning for Stochastic Computation Offloading in Digital Twin Networks. *IEEE Trans. Ind. Inform.* **2020**, *17*, 4968–4977. [CrossRef]
66. Sodhro, A.H.; Rodrigues, J.J.; Pirbhulal, S.; Zahid, N.; de Macedo, A.R.L.; de Albuquerque, V.H.C. Link optimization in software defined IoV driven autonomous transportation system. *IEEE Trans. Intell. Transp. Syst.* **2020**, *22*, 3511–3520. [CrossRef]
67. Hui, Y.; Su, Z.; Luan, T.H. Collaborative content delivery in software-defined heterogeneous vehicular networks. *IEEE/ACM Trans. Netw.* **2020**, *28*, 575–587. [CrossRef]
68. Maity, I.; Dhiman, R.; Misra, S. MobiPlace: Mobility-Aware Controller Placement in Software-Defined Vehicular Networks. *IEEE Trans. Veh. Technol.* **2021**, *70*, 957–966. [CrossRef]
69. Ghimire, B.; Rawat, D.B.; Liu, C.; Li, J. Sharding-Enabled Blockchain for Software-Defined Internet of Unmanned Vehicles in the Battlefield. *IEEE Netw.* **2021**, *35*, 101–107. [CrossRef]
70. Zhang, K.; Cao, J.; Zhang, Y. Adaptive Digital Twin and Multi-agent Deep Reinforcement Learning for Vehicular Edge Computing and Networks. *IEEE Trans. Ind. Inform.* **2021**, *18*, 1405–1413. [CrossRef]
71. Manogaran, G.; Saravanan, V.; Hsu, C.H. Information-centric content management framework for software defined internet of vehicles towards application specific services. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 4541–4549. [CrossRef]
72. Nguyen, H.X.; Trestian, R.; To, D.; Tatipamula, M. Digital twin for 5G and beyond. *IEEE Commun. Mag.* **2021**, *59*, 10–15. [CrossRef]
73. Wu, Y.; Zhang, K.; Zhang, Y. Digital Twin Networks: A Survey. *IEEE Internet Things J.* **2021**, *8*, 13789–13804. [CrossRef]
74. Deng, Y.; Jiang, H.; Cai, P.; Wu, T.; Zhou, P.; Li, B.; Lu, H.; Wu, J.; Chen, X.; Wang, K. Resource Provisioning for Mitigating Edge DDoS Attacks in MEC-Enabled SDVN. *IEEE Internet Things J.* **2022**, *9*, 24264–24280. [CrossRef]
75. Zhang, X.; Zhong, H.; Cui, J.; Gu, C.; Bolodurina, I.; Liu, L. AC-SDVN: An Access Control Protocol for Video Multicast in Software Defined Vehicular Networks. *IEEE Trans. Mob. Comput.* 2022, *early access.*
76. Darabkh, K.A.; Alkhader, B.Z.; Ala'F, K.; Jubair, F.; Abdel-Majeed, M. ICDRP-F-SDVN: An innovative cluster-based dual-phase routing protocol using fog computing and software-defined vehicular network. *Veh. Commun.* **2022**, *34*, 100453. [CrossRef]
77. Tang, F.; Wen, C.; Luo, L.; Zhao, M.; Kato, N. Blockchain-Based Trusted Traffic Offloading in Space-Air-Ground Integrated Networks (SAGIN): A Federated Reinforcement Learning Approach. *IEEE J. Sel. Areas Commun.* **2022**, *40*, 3501–3516. [CrossRef]
78. Zhao, L.; Bi, Z.; Hawbani, A.; Yu, K.; Zhang, Y.; Guizani, M. ELITE: An intelligent digital twin-based hierarchical routing scheme for softwarized vehicular networks. *IEEE Trans. Mob. Comput.* **2022**, *22*, 5231–5247. [CrossRef]
79. Kumar, M.; Raw, R.S. A Novel Routing Protocol for Hierarchical Software Defined Vehicular Adhoc Network. In Proceedings of the 2022 9th International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 23–25 March 2022; pp. 771–775.
80. Wahid, I.; Tanvir, S.; Hameed, A.; Ahmad, M. Software-Defined Networks and Named Data Networks in Vehicular Ad Hoc Network Routing: Comparative Study and Future Directions. *Secur. Commun. Netw.* **2022**, *2022*, 1270180. [CrossRef]
81. Ghonge, M.M. Software-defined network-based vehicular ad hoc networks: A comprehensive review. In *Software Defined Networking for Ad Hoc Networks*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 33–53.
82. Aljeri, N.; Boukerche, A. A novel proactive controller deployment protocol for 5G-enabled software-defined Vehicular Networks. *Comput. Commun.* **2022**, *182*, 88–97. [CrossRef]
83. Alaya, B.; Sellami, L. Towards the Design of an Efficient and Secure System based on the Software-Defined Network Paradigm for Vehicular Networks. *IEEE Access* **2023**, *11*, 43333–43348. [CrossRef]
84. Wijesekara, P.A.D.S.N.; Sudheera, K.L.K.; Sandamali, G.G.N.; Chong, P.H.J. An Optimization Framework for Data Collection in Software Defined Vehicular Networks. *Sensors* **2023**, *23*, 1600. [CrossRef] [PubMed]
85. Nahar, A.; Das, D.; Das, S.K. SpTFrame: A Framework for Spatio-Temporal Information Aware Message Dissemination in Software Defined Vehicular Networks. In Proceedings of the 24th International Conference on Distributed Computing and Networking, Kharagpur, India, 4–7 January 2023; pp. 254–261.
86. Bilen, T.; Canberk, B.; Duong, T.Q. Digital Twin Evolution for Hard-to-Follow Aeronautical Ad-Hoc Networks in Beyond 5G. *IEEE Commun. Stand. Mag.* **2023**, *7*, 4–12. [CrossRef]
87. Qureshi, H.N.; Masood, U.; Manalastas, M.; Zaidi, S.M.A.; Farooq, H.; Forgeat, J.; Bouton, M.; Bothe, S.; Karlsson, P.; Rizwan, A.; et al. Towards Addressing Training Data Scarcity Challenge in Emerging Radio Access Networks: A Survey and Framework. *IEEE Commun. Surv. Tutor.* **2023**. . [CrossRef]
88. Xu, Y.; Liu, X.; Cui, J.; Zhong, H.; Zhang, J. L-TCM: A Lightweight Privacy-Preserving Traffic Condition Monitoring Scheme with Source Authentication in Cloud-Assisted VANETs. *IEEE Syst. J.* 2023, *early access*.
89. Matiuzzi Stocchero, J.; Dexheimer Carneiro, A.; Zacarias, I.; Pignaton de Freitas, E. Combining information centric and software defined networking to support command and control agility in military mobile networks. *Peer-to-Peer Netw. Appl.* **2023**, *16*, 765–784. [CrossRef]
90. Guo, F.; Peng, M. Efficient Mobility Management in Mobile Edge Computing Networks: Joint Handover and Service Migration. *IEEE Internet Things J.* **2023**, *Early Access*. [CrossRef]

91. Thangaraj, J.; Ravi, B.; Kumari, S. Performance analysis of collision avoidance routing protocol for inter-vehicular communication. *Clust. Comput.* **2019**, *22*, 7769–7775. [CrossRef]
92. Lin, D.; Lin, Z.; Kong, L.; Guan, Y.L. CMSTR: A Constrained Minimum Spanning Tree Based Routing Protocol for Wireless Sensor Networks. *Ad Hoc Netw.* **2023**, *146*, 103160. [CrossRef]
93. Benmir, A.; Korichi, A.; Bourouis, A.; Alreshoodi, M.; Al-Jobouri, L. GeoQoE-Vanet: QoE-aware geographic routing protocol for video streaming over vehicular ad-hoc networks. *Computers* **2020**, *9*, 45. [CrossRef]
94. Wu, C.; Liu, Z.; Liu, F.; Yoshinaga, T.; Ji, Y.; Li, J. Collaborative learning of communication routes in edge-enabled multi-access vehicular environment. *IEEE Trans. Cogn. Commun. Netw.* **2020**, *6*, 1155–1165. [CrossRef]
95. Li, Y.; Wang, X.; Zeng, R.; Donta, P.K.; Murturi, I.; Huang, M.; Dustdar, S. Federated Domain Generalization: A Survey. *arXiv* **2023**, arXiv:2306.01334.
96. Ravi, B.; Thangaraj, J.; Petale, S. Data Traffic Forwarding for Inter-vehicular Communication in VANETs Using Stochastic Method. *Wirel. Pers. Commun.* **2019**, *106*, 1591–1607. [CrossRef]
97. Wei, L.; Cui, J.; Zhong, H.; Bolodurina, I.; Gu, C.; He, D. A Decentralized Authenticated Key Agreement Scheme Based on Smart Contract for Securing Vehicular Ad-hoc Networks. *IEEE Trans. Mob. Comput.* 2023, *early access*.
98. Urmonov, O.; Kim, H. A multi-hop data dissemination algorithm for vehicular communication. *Computers* **2020**, *9*, 25. [CrossRef]
99. Ravi, B.; Thangaraj, J. Stochastic traffic flow modeling for multi-hop cooperative data dissemination in VANETs. *Phys. Commun.* **2021**, *46*, 101290. [CrossRef]
100. Shari, N.F.M.; Malip, A. Blockchain-based decentralized data dissemination scheme in smart transportation. *J. Syst. Archit.* **2023**, *134*, 102800. [CrossRef]
101. Cong, Y.; Xue, K.; Wang, C.; Sun, W.; Sun, S.; Hu, F. Latency-Energy Joint Optimization for Task Offloading and Resource Allocation in MEC-Assisted Vehicular Networks. *IEEE Trans. Veh. Technol.* **2023** . [CrossRef]
102. kumar Pulligilla, M.; Vanmathi, C. An authentication approach in SDN-VANET architecture with Rider-Sea Lion optimized neural network for intrusion detection. *Internet Things* **2023**, *22*, 100723. [CrossRef]
103. Sharma, A.; Awasthi, L.K. Ob-EID: Obstacle aware event information dissemination for SDN enabled vehicular network. *Comput. Netw.* **2022**, *216*, 109257. [CrossRef]
104. Yu, S.; Cao, Q.; Wang, C.; Xu, G.; Ma, H.; Zhu, Y.; Peng, Y.; Jia, Y. Efficient ECC-based Conditional Privacy-preserving Aggregation Signature Scheme in V2V. *IEEE Trans. Veh. Technol.* 2023, *early access*.
105. Chen, C.; Yao, G.; Liu, L.; Pei, Q.; Song, H.; Dustdar, S. A Cooperative Vehicle-Infrastructure System for Road Hazards Detection With Edge Intelligence. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 5186–5198. [CrossRef]
106. Shen, H.; Tian, Y.; Wang, T.; Bai, G. Slicing-Based Task Offloading in Space-Air-Ground Integrated Vehicular Networks. *IEEE Trans. Mob. Comput.* 2023, *early access*.
107. Silva, F.A.; Boukerche, A.; Silva, T.R.; Cerqueira, E.; Ruiz, L.B.; Loureiro, A.A. Information-Driven Software-Defined Vehicular Networks: Adapting Flexible Architecture to Various Scenarios. *IEEE Veh. Technol. Mag.* **2019**, *14*, 98–107. [CrossRef]
108. Chen, S.; Liu, Y.; Ning, J.; Zhu, X. BASRAC: An efficient batch authentication scheme with rule-based access control for VANETs. *Veh. Commun.* **2023**, *40*, 100575. [CrossRef]
109. Li, P.; Liu, G.; Guo, S.; Zeng, Y. Traffic-aware efficient consistency update in NFV-enabled software defined networking. *Comput. Netw.* **2023**, *228*, 109755. [CrossRef]
110. Ahmed, U.; Lin, J.C.W.; Srivastava, G.; Yun, U.; Singh, A.K. Deep active learning intrusion detection and load balancing in software-defined vehicular networks. *IEEE Trans. Intell. Transp. Syst.* **2022**, *24*, 953–961. [CrossRef]
111. Chen, C.; Qiu, T.; Hu, J.; Ren, Z.; Zhou, Y.; Sangaiah, A.K. A congestion avoidance game for information exchange on intersections in heterogeneous vehicular networks. *J. Netw. Comput. Appl.* **2017**, *85*, 116–126. [CrossRef]
112. Ravi, B.; Thangaraj, J. Performance evaluation of multi service provisioning for multi-hop cooperative data dissemination in SDHVN. *J. Ambient Intell. Humaniz. Comput.* **2021**, *13*, 4773–4786. [CrossRef]
113. Song, Y.; Luo, W.; Xu, P.; Wei, J.; Qi, X. An improved Lagrangian relaxation algorithm based SDN framework for industrial internet hybrid service flow scheduling. *Sci. Rep.* **2022**, *12*, 3861. [CrossRef] [PubMed]
114. Gillani, M.; Niaz, H.A.; Farooq, M.U.; Ullah, A. Data collection protocols for VANETs: A survey. *Complex Intell. Syst.* **2022**, *8*, 2593–2622. [CrossRef]
115. Debalki, Y.A.; Hou, J.; Ullah, H.; Adane, B.Y. Multi-hop data dissemination using a multi-metric contention-based broadcast suppression strategy in VANETs. *Ad Hoc Netw.* **2023**, *140*, 103070. [CrossRef]
116. Xiao, K.; Liu, K.; Xu, X.; Zhou, Y.; Feng, L. Efficient fog-assisted heterogeneous data services in software defined VANETs. *J. Ambient Intell. Humaniz. Comput.* **2021**, *12*, 261–273. [CrossRef]
117. Lv, Y.; Zhai, Y.; Li, P.; Cui, J.; Zhou, W. Research on SDN-Based New In-vehicle Network Packet Scheduling Technology. In *Advanced Manufacturing and Automation XI*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 214–222.
118. Karakoç, N.; Scaglione, A.; Reisslein, M.; Wu, R. Federated edge network utility maximization for a multi-server system: Algorithm and convergence. *IEEE/ACM Trans. Netw.* **2022**, *30*, 2002–2017. [CrossRef]
119. Zhou, W.; Xia, J.; Zhou, F.; Fan, L.; Lei, X.; Nallanathan, A.; Karagiannidis, G.K. Profit Maximization for Cache-Enabled Vehicular Mobile Edge Computing Networks. *IEEE Trans. Veh. Technol.* 2023, *early access*. [CrossRef]
120. Gu, L.; Zeng, D.; Tao, S.; Guo, S.; Jin, H.; Zomaya, A.Y.; Zhuang, W. Fairness-aware dynamic rate control and flow scheduling for network utility maximization in network service chain. *IEEE J. Sel.* **2019**, *37*, 1059–1071. [CrossRef]

121. Liu, R.W.; Guo, Y.; Lu, Y.; Chui, K.T.; Gupta, B.B. Deep Network-Enabled Haze Visibility Enhancement for Visual IoT-Driven Intelligent Transportation Systems. *IEEE Trans. Ind. Inform.* **2023**, *19*, 1581–1591. [CrossRef]
122. Parveen; Kumar, S.; Singh, R.P.; Kumar, A.; Yaduwanshi, R.; Dora, D.P. TS-CAGR: Traffic sensitive connectivity-aware geocast routing protocol in internet of vehicles. *Ad Hoc Netw.* **2023**, *147*, 103210. [CrossRef]
123. Liu, J.; Peng, C.; Sun, R.; Liu, L.; Zhang, N.; Dustdar, S.; Leung, V.C. CPAHP: Conditional Privacy-Preserving Authentication Scheme With Hierarchical Pseudonym for 5G-Enabled IoV. *IEEE Trans. Veh. Technol.* **2023**, *72*, 8929–8940. [CrossRef]
124. Ansari, F.; Rehman, R.A.; Arsalan, A. Reduced network forwarding with controller enabled named software defined Internet of Mobile Things. *Ad Hoc Netw.* **2023**, *149*, 103235. [CrossRef]
125. Ravi, B.; Thangaraj, J.; Shandilya, S.K. Stochastic modelling and analysis of mobility models for intelligent software defined internet of vehicles. *Phys. Commun.* **2022**, *50*, 101498. [CrossRef]
126. Bine, L.M.; Boukerche, A.; Ruiz, L.B.; Loureiro, A.A. IoDMix: A novel routing protocol for Delay-Tolerant Internet of Drones integration in Intelligent Transportation System. *Ad Hoc Netw.* **2023**, *148*, 103204. [CrossRef]
127. Zhao, X.; Liu, M.; Li, M. Task offloading strategy and scheduling optimization for internet of vehicles based on deep reinforcement learning. *Ad Hoc Netw.* **2023**, *147*, 103193. [CrossRef]
128. Pujol, V.C.; Donta, P.K.; Morichetta, A.; Murturi, I.; Dustdar, S. Edge Intelligence—Research Opportunities for Distributed Computing Continuum Systems. *IEEE Internet Comput.* **2023**, *27*, 53–74. [CrossRef]
129. Li, Y.; Liang, W.; Li, J.; Cheng, X.; Yu, D.; Zomaya, A.Y.; Guo, S. Energy-Aware, Device-to-Device Assisted Federated Learning in Edge Computing. *IEEE Trans. Parallel Distrib. Syst.* **2023**, *34*, 2138–2154. [CrossRef]
130. Murturi, I.; Dustdar, S. Decent: A decentralized configurator for controlling elasticity in dynamic edge networks. *ACM Trans. Internet Technol. (TOIT)* **2022**, *22*, 1–21. [CrossRef]
131. Govori, E.; Murturi, I.; Dustdar, S. A Comprehensive Performance Evaluation of Procedural Geometry Workloads on Resource-Constrained Devices. In Proceedings of the 2023 IEEE International Conference on Edge Computing & Communication (EDGE), Chicago, IL, USA, 2–8 July 2023; pp. 1–9.
132. Murturi, I.; Egyed, A.; Dustdar, S. Utilizing AI planning on the edge. *IEEE Internet Comput.* **2022**, *26*, 28–35. [CrossRef]
133. Zhou, H.; Jiang, K.; He, S.; Min, G.; Wu, J. Distributed Deep Multi-Agent Reinforcement Learning for Cooperative Edge Caching in Internet-of-Vehicles. *IEEE Trans. Wirel. Commun.* 2023, *early access*. [CrossRef]
134. Rizwan, S.; Husnain, G.; Aadil, F.; Ali, F.; Lim, S. Mobile Edge-based Information-Centric Network for emergency messages dissemination in Internet of Vehicles: A Deep Learning Approach. *IEEE Access* **2023**, *11*, 62574–62590. [CrossRef]
135. Tung, H.Y.; Tsang, K.F.; Chui, K.T.; Tung, H.C.; Chi, H.R.; Hancke, G.P.; Man, K.F. The Generic Design of a High-Traffic Advanced Metering Infrastructure Using ZigBee. *IEEE Trans. Ind. Inform.* **2014**, *10*, 836–844. [CrossRef]
136. Huang, Z.; Li, D.; Cai, J.; Lu, H. Collective reinforcement learning based resource allocation for digital twin service in 6G networks. *J. Netw. Comput. Appl.* **2023**, *217*, 103697. [CrossRef]
137. Li, B.; Shi, Y.; Kong, Q.; Du, Q.; Lu, R. Incentive-Based Federated Learning for Digital Twin Driven Industrial Mobile Crowdsensing. *IEEE Internet Things J.* 2023, *early access*. [CrossRef]
138. Li, J.; Liang, W.; Xu, Z.; Jia, X.; Zhou, W. Service Provisioning for Multi-source IoT Applications in Mobile Edge Computing. *ACM Trans. Sens. Netw. (TOSN)* **2021**, *18*, 1–25. [CrossRef]
139. Chen, B.; Wang, Z.; Xiang, T.; Yang, J.; He, D.; Choo, K.K.R. BCGS: Blockchain-assisted privacy-preserving cross-domain authentication for VANETs. *Veh. Commun.* **2023**, *41*, 100602. [CrossRef]
140. Wang, B.; Zheng, J.; Ren, Q.; Li, C. Analysis of IEEE 802.11p-Based Intra-platoon Message Broadcast Delay in a Platoon of Vehicles. *IEEE Trans. Veh. Technol.* 2023, *early access*. [CrossRef]
141. Thiruvasagam, P.K.; Kotagi, V.J.; Murthy, C.S.R. The More the Merrier: Enhancing Reliability of 5G Communication Services With Guaranteed Delay. *IEEE Netw. Lett.* **2019**, *1*, 52–55. [CrossRef]
142. Halabian, H.; Lambadaris, I.; Viniotis, Y. Optimal server assignment in multi-server queueing systems with random connectivities. *J. Commun. Netw.* **2019**, *21*, 405–415. [CrossRef]
143. Singh, D.; Ng, B.; Lai, Y.C.; Lin, Y.D.; Seah, W.K. Modelling software-defined networking: Switch design with finite buffer and priority queueing. In Proceedings of the 2017 IEEE 42nd Conference on Local Computer Networks (LCN), Singapore, 9–12 October 2017; pp. 567–570.
144. Liu, K.; Ng, J.K.; Lee, V.; Son, S.H.; Stojmenovic, I. Cooperative data scheduling in hybrid vehicular ad hoc networks: VANET as a software defined network. *IEEE/ACM Trans. Netw. (TON)* **2016**, *24*, 1759–1773. [CrossRef]
145. Li, H.; Ou, D.; Rasheed, I.; Tu, M. A Software-Defined Networking Roadside Unit Cloud Resource Management Framework for Vehicle Ad Hoc Networks. *J. Adv. Transp.* **2022**, *2022*, 5918128. [CrossRef]
146. Liu, L.; Yuan, X.; Zhang, N.; Chen, D.; Yu, K.; Taherkordi, A. Joint Computation Offloading and Data Caching in Multi-Access Edge Computing Enabled Internet of Vehicles. *IEEE Trans. Veh. Technol.* 2023, *early access*.
147. Awada, U.; Zhang, J.; Chen, S.; Li, S.; Yang, S. Resource-aware multi-task offloading and dependency-aware scheduling for integrated edge-enabled IoV. *J. Syst. Archit.* **2023**, *141*, 102923. [CrossRef]
148. Bilen, T.; Ayvaz, K.; Canberk, B. QoS-based distributed flow management in software defined ultra-dense networks. *Ad Hoc Netw.* **2018**, *78*, 24–31. [CrossRef]

149. Mahmood, A. Towards Software Defined Heterogeneous Vehicular Networks for Intelligent Transportation Systems. In Proceedings of the 2019 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), Kyoto, Japan, 11–15 March 2019; pp. 441–442.
150. Kumar, A.; Abdelhadi, A.; Clancy, T.C. *Design and Implementation of Practical Schedulers for M2M Uplink Networks: Using MATLAB*; Springer: Berlin/Heidelberg, Germany, 2018.
151. Ye, Q.; Zhuang, W.; Li, X.; Rao, J. End-to-end delay modeling for embedded VNF chains in 5G core networks. *IEEE Internet Things J.* **2018**, *6*, 692–704. [CrossRef]
152. Zhang, X.; Chang, Z.; Hu, T.; Chen, W.; Zhang, X.; Min, G. Vehicle Selection and Resource Allocation for Federated Learning-Assisted Vehicular Network. *IEEE Trans. Mob. Comput.* 2023, *early access*.
153. Kumar, A.S.; Zhao, L.; Fernando, X. Task Offloading and Resource Allocation in Vehicular Networks: A Lyapunov-based Deep Reinforcement Learning Approach. *IEEE Trans. Veh. Technol.* 2023, *early access*. [CrossRef]
154. Basu, D.; Kal, S.; Ghosh, U.; Datta, R. DRIVE: Dynamic Resource Introspection and VNF Embedding for 5G using Machine Learning. *IEEE Internet Things J.* 2023, *early access*.
155. Guo, H.; Wang, Y.; Liu, J.; Liu, C. Multi-UAV Cooperative Task Offloading and Resource Allocation in 5G Advanced and Beyond. *IEEE Trans. Wirel. Commun.* 2023, *early access*. [CrossRef]
156. Khalfaoui, H.; Azmani, A.; Farchane, A.; Safi, S. Symbiotic Combination of a Bayesian Network and Fuzzy Logic to Quantify the QoS in a VANET: Application in Logistic 4.0. *Computers* **2023**, *12*, 40. [CrossRef]
157. Yang, C.P.; Yen, C.E.; Chang, I.C. A Software-Defined Directional Q-Learning Grid-Based Routing Platform and Its Two-Hop Trajectory-Based Routing Algorithm for Vehicular Ad Hoc Networks. *Sensors* **2022**, *22*, 8222. [CrossRef]
158. Gonçalves, D.M.; Puliafito, C.; Mingozzi, E.; Bittencourt, L.F.; Madeira, E.R. End-to-end network slicing in vehicular clouds using the MobFogSim simulator. *Ad Hoc Netw.* **2023**, *141*, 103096. [CrossRef]
159. Tahmasebi, A.; Salahi, A.; Pourmina, M.A. Improvement of Software-Defined Network Performance Using Queueing Theory: A Survey. *Majlesi J. Telecommun. Devices* **2021**, *10*, 33–43. [CrossRef]
160. Ju, Y.; Chen, Y.; Cao, Z.; Liu, L.; Pei, Q.; Xiao, M.; Ota, K.; Dong, M.; Leung, V.C. Joint secure offloading and resource allocation for vehicular edge computing network: A multi-agent deep reinforcement learning approach. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 5555–5569. [CrossRef]
161. Nazari, A.; Kordabadi, M.; Mohammadi, R.; Lal, C. EQRSRL: An energy-aware and QoS-based routing schema using reinforcement learning in IoMT. *Wirel. Netw.* **2023**, 1–15. [CrossRef]
162. Boualouache, A.; Engel, T. A survey on machine learning-based misbehavior detection systems for 5g and beyond vehicular networks. *IEEE Commun. Surv. Tutor.* **2023**, *25*, 1128–1172. [CrossRef]
163. Donta, P.K.; Sedlak, B.; Casamayor Pujol, V.; Dustdar, S. Governance and sustainability of distributed continuum systems: A big data approach. *J. Big Data* **2023**, *10*, 1–31. [CrossRef]
164. Baccour, E.; Allahham, M.S.; Erbad, A.; Mohamed, A.; Hussein, A.R.; Hamdi, M. Zero Touch Realization of Pervasive Artificial Intelligence as a Service in 6G Networks. *IEEE Commun. Mag.* **2023**, *61*, 110–116. [CrossRef]