IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 3 November 2023, accepted 11 December 2023, date of publication 15 December 2023, date of current version 20 December 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3343613

RESEARCH ARTICLE

Federated Learning Enabled SDN for Routing Emergency Safety Messages (ESMs) in IoV Under 5G Environment

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ABSTRACT The emerging fifth-generation (5G) technology towards Internet of Vehicles (IoV) provides numerous advantages, such as lower levels of latency, stable link connections, and support for high mobility. However, avoiding vehicle collisions in IoV is a challenging task due to routing Emergency Safety Messages (ESMs) without strict delay and reliability requirements. To address this issue, we propose a novel intelligent Software-Defined Networking-based Collision Avoidance (SDNCA) framework assisted 5G. Primarily, SDNCA performs the first algorithm that accurately estimates the Risk Severity (RS) value for each vehicle via training the proposed Risk Severity-Artificial Neural Network (RS-ANN) model through the implementation of federated learning among vehicles. The SDNCA framework applies the second algorithm to achieve three main objectives. First, it calculates the Quality of Service (QoS) of the ESM based on RS, Vehicle Speed (VS), and Risk Distance (RD). Second, it dynamically allocates 5G network and computing resources (gNB_{nr_i} and gNB_{cr_i}) for three Virtual Networks (VNs) based on QoS, RD, and VS. Third, it selects the best route (best gNB) for routing the ESMs from the Source Vehicle (SV) to the Destination Vehicle (DV). To ensure effective forwarding for each ESM, SDNCA deploys the third algorithm at the selected gNB to schedule the ESMs considering their priorities and configures the gNB_{nr_i} and gNB_{cr_i} based on the OpenFlow control message received from the SDN. The real-time simulation results demonstrate that the SDNCA framework achieves the ideal values of 17% Network Overhead (NO) and Computational Complexity (CC), a remarkable 0% Collision Rate (CR), 18 ms End-to-End (E2E) Delay, and 89%–90% Packet (ESM) Transmission Reliability (TR) compared with the existing related research.

INDEX TERMS 5G-IoV, beamforming, collision avoidance, emergency safety messages, federated learning, multi access edge computing, network function virtualization, software defined networking.

I. INTRODUCTION

Technological transformations in automated vehicles are leading to vital changes in the transport systems and automotive industries due to their rapid proliferation on roads, contributing to increased safety and effectiveness [1], [2], [3]. Recently, the concept of the Internet of Vehicles (IoV) [4] has drawn significant attention as a promising approach to reduce traffic accidents, alleviate traffic congestion, and provide various convenient applications, such as autonomous driving, interactive entertainment, and real-time traffic information [5], [6].

The IoV connects hardware devices, network communication channels, and cloud platforms that allow connected vehicles, pedestrians, and intelligent units near the road to exchange information in real-time [7], [8], [9], [10]. Autonomous vehicles (AVs) are nearing commercialization and are expected to become dominant among various emerging vehicles in the future [11], [12]. Wireless communication technologies, specifically vehicular communications such as Vehicle-to-Everything (V2X) [13], along with existing vehicle-sensing capabilities [14], provide support for enhanced safety applications, thereby enabling AVs for safer autonomous driving [15]. The important supporting technologies of artificial intelligence (AI) [16] and fifth-generation (5G) networks [17], [18] in IoV technology are

The associate editor coordinating the review of this manuscript and approving it for publication was Sangsoon Lim.

considered potential solutions for boosting vehicular critical safety applications [19].

IoV based on 5G communication (5G-IoV) enables Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Roadside (V2R), Vehicle-to-Pedestrian (V2P), Vehicle-to-Grid (V2G), Vehicle-to-Building (V2B), Vehicle-to-Device (V2D), and Vehicle-to-Cloud (V2C) communication modes with high data rates and very low latency, making AVs a reality [20]. Beamforming and virtualization technologies are considered the best solutions to optimize 5G utilization in IoV. Beamforming design aims to reduce the hardware and signal processing complexity while achieving near-optimal performance by directing a narrow beam toward each vehicle destination. Thus, adaptive beamforming can minimize interference, improve network coverage, and increase throughput [21]. Conversely, Network Function Virtualization (NFV) is an underlying method that enables network operators to create network slices per end-user application or service requirement with guaranteed performance and quality corresponding to service-level agreements [22]. Thus, emerging 5G-IoV supports high-speed mobility, broad coverage, substantial capacity, and a stable connection [23]. These attributes are effective for enabling V2X services, particularly in satisfying the stringent latency requirements of safety-critical missions such as autonomous driving [24]. Although 5G-IoV aims to provide new capabilities and strict Quality of Service (QoS) requirements, it runs its network functions over a unified operating system, particularly at its edge [25].

Mobile Edge Computing/Multiaccess Edge Computing (MEC) has been envisioned for future 5G-IoV, in which some core network functionalities are moved to the network edge, that is, nearer to the vehicles for lower latency and local processing of sensitive data for critical public safety services [26]. However, MEC requires the virtualization of network infrastructure for the utilization of cloud resources at the network edge. As Software-Defined Networking (SDN) [27] provides flexibility in network management and large-scale optimization with unified abstraction [28], [29], SDN is combined with MEC to control virtual network (VN) customization [30]. In addition, MEC can be utilized to bolster the control of SDN in the 5G-IoV, improving network and resource management [31]. Thus, the supportive 5G-IoV introduces resilience, elasticity, QoS provisioning, and programmability by efficiently allocating the available 5G resources and minimizing network management latency [32], [33]. Moreover, the central SDN controller can manage edge servers deployed at 5G base stations [34]. Therefore, SDN can achieve reliable transmission of Emergency Safety Messages (ESMs) to the destination vehicles in the 5G-IoV environment [35].

ESMs are emergency warnings and delay-sensitive messages transmitted to the targeted vehicles when detecting hazardous events on the road to avoid crucial danger and road congestion [36]. The major challenge of ESM dissemination in traditional vehicular networks is high broadcast storms, which consume large amounts of bandwidth, increase network congestion, and further increase dissemination delay [37]. Moreover, the QoS provisioning regarding the reliability of the surrounding vehicles that can receive safety messages from a transmitting vehicle within the message lifetime still has several limitations in high-density IoV scenarios and uneven traffic distributions [38], [39]. The reason can be attributed to the numerous challenges that vehicular networks face, such as channel interference, limited bandwidth, line-of-site (LOS) and non-line-of-site (NLOS) connections, highly dynamic mobility scenarios, and environmental changes [40]. At the same time, the large amount of data collected by sensors requires high processing and communication capabilities [41]. To alleviate the broadcast storm problem and handle the challenges in vehicular networks, SDN-assisted 5G-IoV technology requires the integration of AI techniques [42].

Federated learning (FL), a promising framework [43], is considered a feasible solution for safety-and time-critical applications involving AVs [44], [45], [46]. Considering FL in IoV [47], the vehicles will train and improve the initial downloaded model using their local data and send the resulting model parameters to the edge servers and then to the central server for global aggregation [48]. The essential communication between the edge server and federated vehicles can be either synchronous FL (SFL) or asynchronous FL (AFL) [49]. Recent studies have investigated the application of FL in SDN controller, and the central SDN server in this case is used to coordinate the edge servers associated with 5G base stations and aggregate the learning model updates received from these edge servers [50].

However, to the best of our knowledge, no research has used FL to enable the SDN controller to implement three objectives for the purpose of routing ESMs in 5G-IoV. To overcome the aforementioned bottlenecks, and specifically provide effective coordination and boost safety-critical services in 5G-V2I communication, we propose a novel Software-Defined Networking-based Collision Avoidance (SDNCA) framework for routing the ESMs from the Source Vehicle (SV) to the Destination Vehicle (DV) via 5G technology to avoid vehicle collisions. The key contributions of the proposed framework are as follows:

- The novelty of the proposed SDNCA framework lies in the implementation of four technologies (i.e., 5G, FL, MEC, and SDN) in IoV environment. The SDNCA framework employs three proposed algorithms (Algorithms 1–3) for routing ESMs to avoid vehicle collisions by controlling network congestion.
- We propose a Vehicular Federated Learning (VFL) algorithm (Algorithm 1) for improved estimation of the Risk Severity (RS) of vehicles. This algorithm estimates RS for each vehicle by training the proposed AI model (Risk Severity-Artificial Neural Network (RS-ANN) model) through federated learning

between vehicles. This method of learning enhances the training and test accuracies, and provides lower training and test latencies.

- On the basis of Algorithm 1, we formulate a novel SDN algorithm (Algorithm 2) to handle three main successive objectives in an OpenFlow control message. First, it identifies the QoS for each ESM by (5). Second, it dynamically allocates 5G network and computing resources (gNB_{nr_i} and gNB_{cr_i}) based on the QoS value, Risk Distance (RD), and Vehicle Speed (VS). Third, it traces the best route (best gNB) for routing ESMs from SV to DV. Algorithm 2 handles each ESM independently in an efficient manner, which controls the network congestion.
- Algorithm 3 is then proposed at the selected gNB to schedule ESMs based on their priorities using (10). It also configures the gNB_{nr_i} and gNB_{cr_i}. In this way, the selected gNB forwards ESMs to the DV with low latency and extremely high reliability, thereby avoiding vehicle collisions.
- The real-time simulation results indicate that the SDN controller in our SDNCA framework can optimize the network communication of ESMs to vehicles in 5G-IoV through the FL scheme.

The rest of the paper is organized as follows: Section II explains the related research papers along with their limitations. Section III demonstrates the specific problem statement. Section IV describes the proposed architecture. Section V briefly describes the proposed SDNCA framework using the proposed algorithms. Section VI presents the simulation scenarios and evaluates the performance of various phases implemented in the SDNCA. Section VII concludes the study and provides future research directions.

II. RELATED RESEARCH

In recent years, increasing safety by transmitting ESMs to vehicles has become a challenge. This section provides related research on safety message dissemination in vehicular networks based on three categories. The most relevant studies are summarized in Table 1.

A. TRADITIONAL IEEE 802.11P PROTOCOL-ENABLED ESMS DISSEMINATION

Short-range V2V and V2R communications [51] are basic vehicular communications that are enabled through the IEEE 802.11p protocol/WAVE [52], [53]. The dedicated spectrum for this protocol is 75 MHz in the range of 5.850–5.925 GHz [54], [55]. One of the main problems using IEEE 802.11p technology in emergency traffic situations is broadcast storms, which have been addressed in the literature [56], [57], [58], [59], and [60] using various mechanisms. The clustering technique was introduced in [56], [58], and [60] to reduce broadcast storms and disseminate ESMs by choosing a forwarder that has higher compatible interests with other vehicles in [56]. This forwarder disseminates ESMs to vehicles near the accidental region, thereby attaining ESM dissemination over time. However, the researchers in [58] allowed only the furthest vehicles to rebroadcast ESMs after a certain time barrier expiration, which resulted in less network congestion. [60] outperformed [58] by examining the link stable estimation parameter and achieving improved results. The protocol in [57] strengthened reliability by evaluating each vehicle's transmission probability concerning distance, packet reception ratio, and link availability metrics. The vehicle with the highest value forwards the ESM, with other vehicles as backups in case of failure. In [59], SDN managed network loads, and different ML classifiers detected accident events, whereas selected forwarders (RSU and vehicles) transmitted ESMs based on nearby vehicle information with the help of SDN, thereby improving routing efficiency. ESM delivery at intersections was evaluated in [61], which obtained vehicles at extreme positions and hidden zones. Subsequently, a modified PSO algorithm is proposed to adjust multiple transmission factors with improved performance to offer highly reliable vehicular safety services. In [62], a TDMA-based MAC protocol was utilized to disseminate ESMs. The protocol controls the collisions by setting the transmission powers dynamically based on the transmission ranges and thus achieves a high QoS for safety applications. The protocol proposed in [63] was used to alleviate the burden of DSRC and guarantee reliability. The protocol prioritizes the ESM transmission from a vehicle based on accident risk evaluation, which calculates the distance between the vehicle and the danger zone and hence transmits ESMs with higher reliability. The Temporary Warning Network (TWN) concept developed in [64] focused on improving the coverage and duration of ESM dissemination. The selection of the forwarder vehicles was based on their correlated space-time information. The forwarder vehicles achieved efficient performance.

B. 5G-ENABLED ESMS DISSEMINATION

Data dissemination in vehicular networks, especially ESM dissemination, is one of the main challenges that needs to be identified [65]. The low-latency feature of 5G technology [66], [67] is helpful in this context, particularly in V2I communication, which enables the reliable transmission of ESMs to vehicles on time [68]. A few 5G-V2X-related schemes are explained in this section. Studies [69] and [70] handled link and packet losses by transmitting ESMs over Device-to-Device (D2D) communication. The routing mechanism selects the best forwarder utilizing the Bayesian rule-based fuzzy logic (BRFL) and stable matching (SM) algorithms in [69] and [70], respectively, which improves the QoS. In [71], the authors reviewed in detail the latest contributions for ESM dissemination in vehicular networks in a 5G environment. They also highlighted the different implemented mechanisms based on SDN and fog computing. The DDQN algorithm in [72] adjusted the ESM transmitting rate by calculating the risk distance between vehicles to mit-

TABLE 1. Summary of the most related prior research.

Ref.	**Evaluation Metrics:** Packet Delivery Ratio (PDR), End-to-End delay (E2E delay), Network Overhead (NO), Computational Complexity (CC), Collision Rate (CR)	**Major Limitations**
[69]	PDR, throughput, transmission delay, dissemination delay	The dissemination delay of ESMs over D2D communication is not considered.
[70]	Throughput, PDR, E2E delay, emergency information coverage, packet transmission reliability	Lack of specific analysis of ESM transmission reliability in terms of vehicle density and vehicle speed.
[73]	Dissemination delay of ESMs is in terms of backhaul latency and the distance of the targeted vehicle from the relevance area	Forwarder selection considering only SRs was insufficient for improving the overall network performance.
[74]	NO, CC, PDR, CR, dissemination efficiency, E2E delay	The effectiveness of this system model decreases as the number of vehicles increases.

igate channel congestion. The proposed algorithm satisfies each vehicle's requested resources and maintains safe communication among vehicles. The authors in [73] introduced a boosted routing framework based on social relationships (SRs) for ESM dissemination. SDN and MEC have been utilized in managing these SRs to improve ESM delivery. The SDN implemented a federated k-means algorithm to cluster vehicles in [74] to provide efficient ESM transmission. SDN reduces network congestion by transmitting ESMs to the selected cluster head (CH). The CH then delivers the ESMs to all its members in single-hop communication.

C. SDN-ENABLED ESMS DISSEMINATION

Recently, SDN has been deployed in vehicular networks to boost many services, including safety [75]. The major problem that occurs during emergencies is the need to reduce the time taken to analyze the on-location situation to reduce traffic congestion and facilitate critical-time safety information dissemination [76]. [59], [71], [73], [74] proposed the SDN paradigm for ESM dissemination due to its ability to reduce routing overhead.

III. SPECIFIC PROBLEM STATEMENT

This section signifies the problems present in the existing ESM dissemination approaches associated with the IEEE 802.11p, 5G, and SDN technologies that hinder resolving the vehicle collision problem.

The proposed SDNCA framework focuses on a specific problem, that is, avoiding vehicle collisions by routing ESMs from SV to DV through the three proposed algorithms (Algorithms 1–3). The issues identified in existing studies include the following:

- ESM dissemination is highly bandwidth-intensive due to broadcast storms. Therefore, the existing solutions in Section II-A cannot satisfy the requirements of transmitting ESMs to vehicles with high reliability and low latency, which require high-speed network access.
- The integration of IEEE 802.11p and 5G technologies in [69] and [70] in Section II-B elevates the complexity and network congestion due to beacon messages and network signal transmission. One of the main targets of 5G-IoV is to avoid accidents involving vehicles that require intelligent dynamic control for 5G BSs (5G gNBs). The other existing studies that used 5G technology in this section did not consider this point when transmitting ESMs.
- Using SDN for ESM dissemination in vehicular networks is operationally expensive. Therefore, efficient mechanisms are required to reduce the overall network overhead and operational costs, an aspect not addressed in the studies mentioned in Section II-C.
- Some of the mentioned works used the clustering technique, where the formation and modification of clusters for each ESM transmission increased the network overhead.

IV. PROPOSED ARCHITECTURE

The proposed cellular 5G-V2I framework based on SDN was used to optimize the network communication of ESMs to vehicles in highway scenarios. The proposed architecture shown in Fig. 1 comprises edge and backbone layers. The edge layer is responsible for collecting information about the environment (including traffic, vehicle speed, risks, obstacles, and weather) and the system state (e.g., latency, channel usage, and packet loss). The edge layer consists of the following:

- vehicles enabled with 5G technology (V_1, V_2, $V_3 \ldots\ldots V_N$);
- multiple 5G BSs; 5G gNBs (gNB_{E1}, gNB_{E2}, gNB_{E3}, ... gNB_{EM}), which are responsible for intra-communication and routing; and 5G gNBs cores ($gNB_{C1}, gNB_{C2}, gNB_{C3}, \ldots\ldots\ldots gNB_{CK}$), which are used for inter-communication through the backbone layer and to receive OpenFlow control messages from the SDN controller; and
- Edge Server (ES) for computing and storage processes.

By contrast, the backbone layer interconnects the different 5G edge BSs, providing high-speed routes for transmitting ESMs. The backbone layer includes the following:

- The SDN controller makes the routing and scheduling decisions. The decisions are sent as OpenFlow control messages to the OpenFlow switches. Every networking

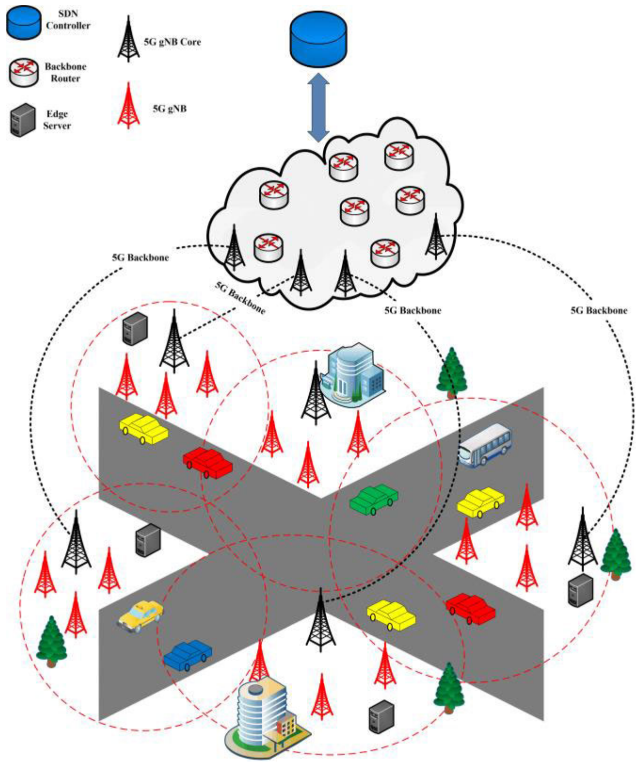

FIGURE 1. SDN-enabled 5G-V2I proposed architecture.

device can act as an OpenFlow switch (e.g., gNBs and routers).

- Backbone routers are used to communicate with the SDN controller and forward traffic between different 5G edge BSs.
- The 5G gNBs are used to communicate with the edge layer.

In this study, we assume that the vehicles move at an initial speed VS_1 to the destination. At a particular time t_i ($i = 1,2,3,\ldots.$) during T, when a vehicle V_i is driving in a real road environment, it faces many circumstances that require it to control its speed and change its direction to avoid accidents and congestion. The proposed framework in Fig. 3 shows how vehicles deal with these circumstances and avoid collisions. Table 2 provides the main notations used in this study.

V. OVERVIEW OF THE PROPOSED SDN-BASED COLLISION AVOIDANCE (SDNCA) FRAMEWORK

Each vehicle in the proposed framework (Fig. 3) is composed of a sensor module that allows the sensor user to interact with the environment and collect system state information (e.g., latency, packet loss, channel usage, interference, and vehicle speed). We define the information data for each vehicle in a tuple format. The tuple has (O, W, VS, RD, RC, and T), and the definition of the tuple is illustrated in Table 2. Each tuple is transmitted after preprocessing to the AI module (ANN module) implemented in the vehicles to train the AI model (RS-ANN model, as shown in Fig. 2) through VFL.

TABLE 2. Main notations.

NOTATION	DESCRIPTION
N	The number of vehicles
M	The number of edge gNBs
K	The number of core gNBs
V_i	$V_1, V_2, V_3, \ldots.V_N$
gNB_{Ei}	$gNB_{E1}, gNB_{E2}, gNB_{E3}, \ldots\ldots.gNB_{EM}$
gNB_{Ci}	$gNB_{C1}, gNB_{C2}, gNB_{C3}, \ldots\ldots.gNB_{CK}$
gNB_{nr_i}	Network resources of any gNB at time t_i
gNB_{cr_i}	Computing resources of any gNB at time t_i
VNs	Virtual Networks
B, MAX.B	Bandwidth, maximum Bandwidth
R, MAX.R	Bitrate, maximum Bitrate
A, MAX.A	Number of Antennas, maximum number of Antennas
M, MAX.M	Utilized Memory, maximum Memory
C, MAX.C	Utilized CPU, maximum CPU
ES	Edge Server at the edge layer
O	Obstacle: It means that the road can be free, slow, or blocked. This feature is represented by random values of 0, 1, and 2.
W	Weather: which represents the weather; it can be good or bad. This feature is represented by random values of 0 and 1.
VS	Vehicle Speed: the speed of the vehicles, which is considered low, medium, or high speed. This feature is represented by random values of 0, 1, and 2.
RD	Risk Distance: the distance to the risk that is considered close, medium, or far. This feature is represented by random values of 0, 1, and 2.
RC	Road Condition: it can be poor, good, or excellent. This feature is represented by random values of 0, 1, and 2.
T	Time: the time of the day during which the ESM is generated, if it is daytime or nighttime. This feature is represented by random values of 0 and 1.
LDB_V	Learning Database at the vehicle
SV	Source Vehicle: the vehicle sending ESM
DV	Destination Vehicle: any vehicle at risk in any direction
RS	Risk Severity (scale of 10): it takes a range of 10 values (0–9)
ANN	Artificial Neural Network
RS-ANN	Risk Severity-Based Artificial Neural Network
PR	Positive Risk
VFL	Vehicular Federated Learning
α_i	Updated local learning model of V_i
β_{t_i}	Latest update of global learning model of ES at t_i
β_{t_i+1}	Updated global learning model of ES at t_i
SDNCA	SDN-Based Collision Avoidance

The RS label is calculated initially as follows:

$$RS = O + W + VS + RD + RC + T \tag{1}$$

If $RS \geq 10$, we reduce the value of the feature by $\boldsymbol{O} = \boldsymbol{O} - (\boldsymbol{RS} - 9)$ if the $\boldsymbol{O}$ feature has the highest value that causes $\boldsymbol{RS} \geq 10$, and we use the same procedure for all other features.

On the basis of the received tuple, the AI module predicts whether the tuple is considered a positive risk (PR) to the vehicles. If the resulted prediction (RS) is ≥ 5, then it is considered a PR; in either case, the data will be stored in a learning database (LDB_V), which will be used to train the AI model, and an ESM is generated along with the information summary, which is (SV, DV, RS, VS, RD, defined tuple). The generated ESM is transmitted to the SDN controller through 5G gNB.

A. PROPOSED VEHICULAR FEDERATED LEARNING (VFL)

The proposed VFL method is shown in Fig. 4. We propose an ANN to build a VFL algorithm (Algorithm 1) using SFL. First, the ES creates a baseline model called the RS-ANN model, as shown in Fig. 2, and sends it to the vehicles. The vehicles use their own dataset (O, W, VS, RD, RC, and T) to train and improve the model for more accurate prediction of the proposed target (RS), and the updated learning models ($\boldsymbol{\alpha_i}$) of the vehicles are transmitted to the ES. The ES aggregates the model updates received from the vehicles and returns the global model ($\boldsymbol{\beta_{t_i}}$) to the vehicles in each training round. Following (2) (general formula [44]), the process is repeated until the model converges. In this study, we use (4) to calculate ($\boldsymbol{\beta_{t_i+1}}$). The SDN then performs its objectives (Section V-B) based on these model updates.

$$\beta_{t_i+1} = \beta_{t_i} + \sum\nolimits_{i=1}^{N} \frac{|D_i|}{|D|}(\alpha_i) \tag{2}$$

where α_i is calculated in this paper by:

$$\alpha_i = \text{local learning model of} V_i - \beta_{t_i} \tag{3}$$

$$\beta_{t_i+1} = \beta_{t_i} + \sum\nolimits_{j=1}^{no.of\ epochs} \sum\nolimits_{i=1}^{N} \frac{(\alpha_i)}{(i+1)\times(j+1)} \tag{4}$$

B. PROPOSED SDN-BASED COLLISION AVOIDANCE APPLICATION

The SDN controller receives the ESM along with the information summary (SV, DV, RS, VS, RD, defined tuple). In this study, the SDN controller focuses on three objectives to transmit ESM to a destination with low latency and high reliability, as illustrated in Algorithm 2. Algorithm 2 explains the objectives of the SDN controller, which are summarized in sequential order.

1) SDN-ENABLED QOS

The SDN controller enables the 5G gNB to schedule messages based on their priorities. The QoS value is based on RS, RD, and VS, and it is calculated using the following proposed equation:

$$QoS = \frac{RS + VS}{RD} \tag{5}$$

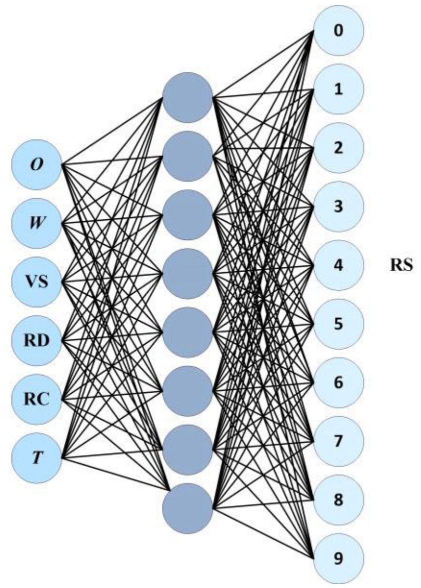

FIGURE 2. RS-ANN Model.

Algorithm 1 Proposed VFL Algorithm for Scenario 1 and Scenario 2

Input: dataset (O, W, VS, RD, RC, T), learning model information
Output: training latency of the model, test latency of the model, train_loss, test_loss, update learning model (β)

```
Initialization: neural network parameters, optimizer,
 baseline_model of ES, latency, train_loss, test_loss
    for no. of epochs
        for each vehicle do
            train the baseline_model based on the given
            dataset
            calculate train_loss
            evaluate the model
            calculate test_loss
            calculate accuracy
            each vehicle uploads its learning updates α_i
            to the ES
          measure the latency of the model
      end for
   update the global model (β) based on (4)
   send β to the vehicles
   train and test β on each vehicle
   calculate train_loss, train_latency, train_accuracy,
  test_loss, test_latency, test_accuracy
end for
```

Thus, QoS will be the highest if RS is high, VS is high, and RD is low.

2) SDN-ENABLED 5G COMMUNICATION

In this study, the 5G network and hardware functions are virtualized. We use three gNBs, and three VNs are created in each gNB (VN_1 for high QoS values, VN_2 for medium

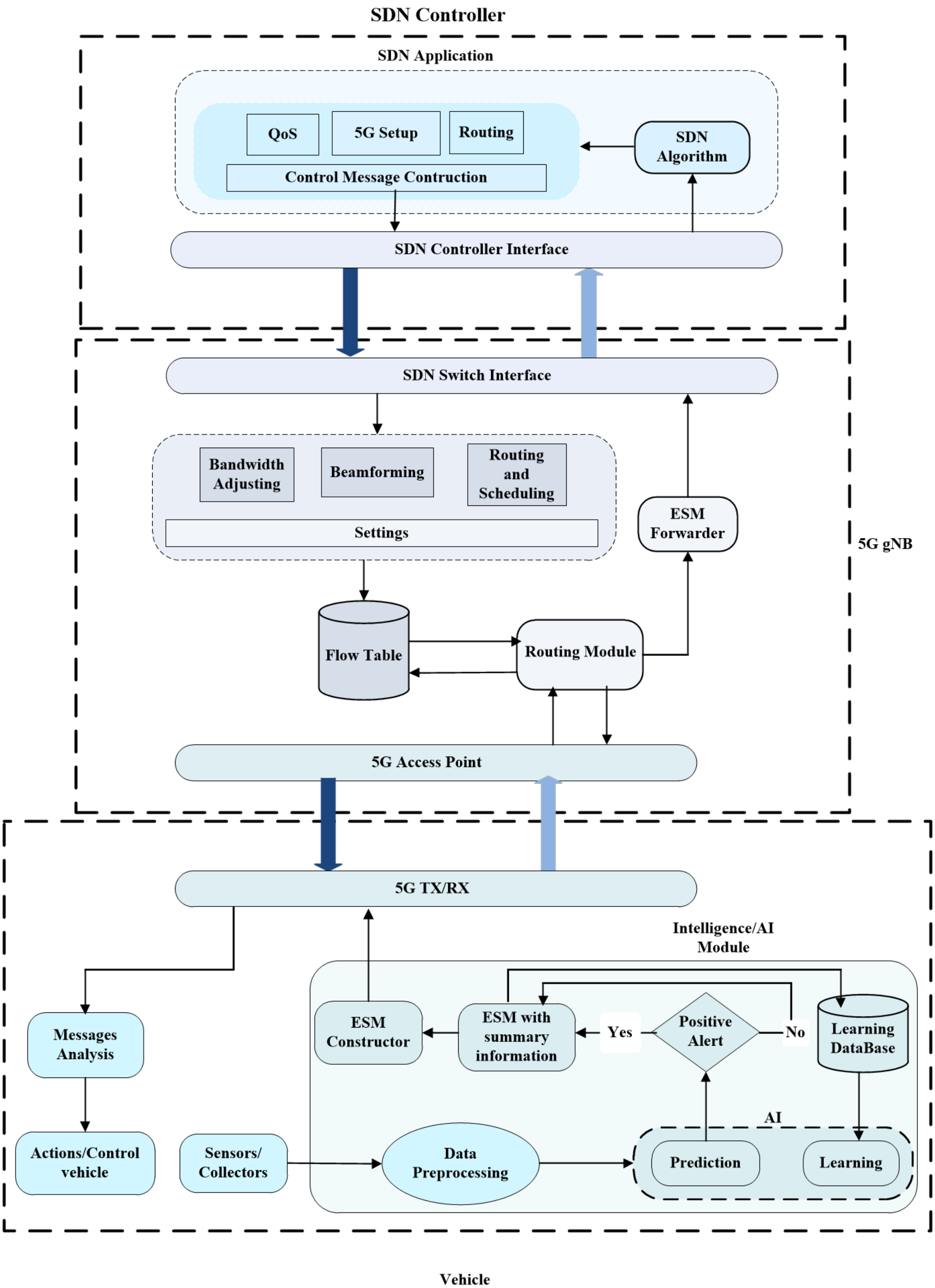

FIGURE 3. Proposed SDN-based Collision Avoidance (SDNCA) Framework in 5G-V2I.

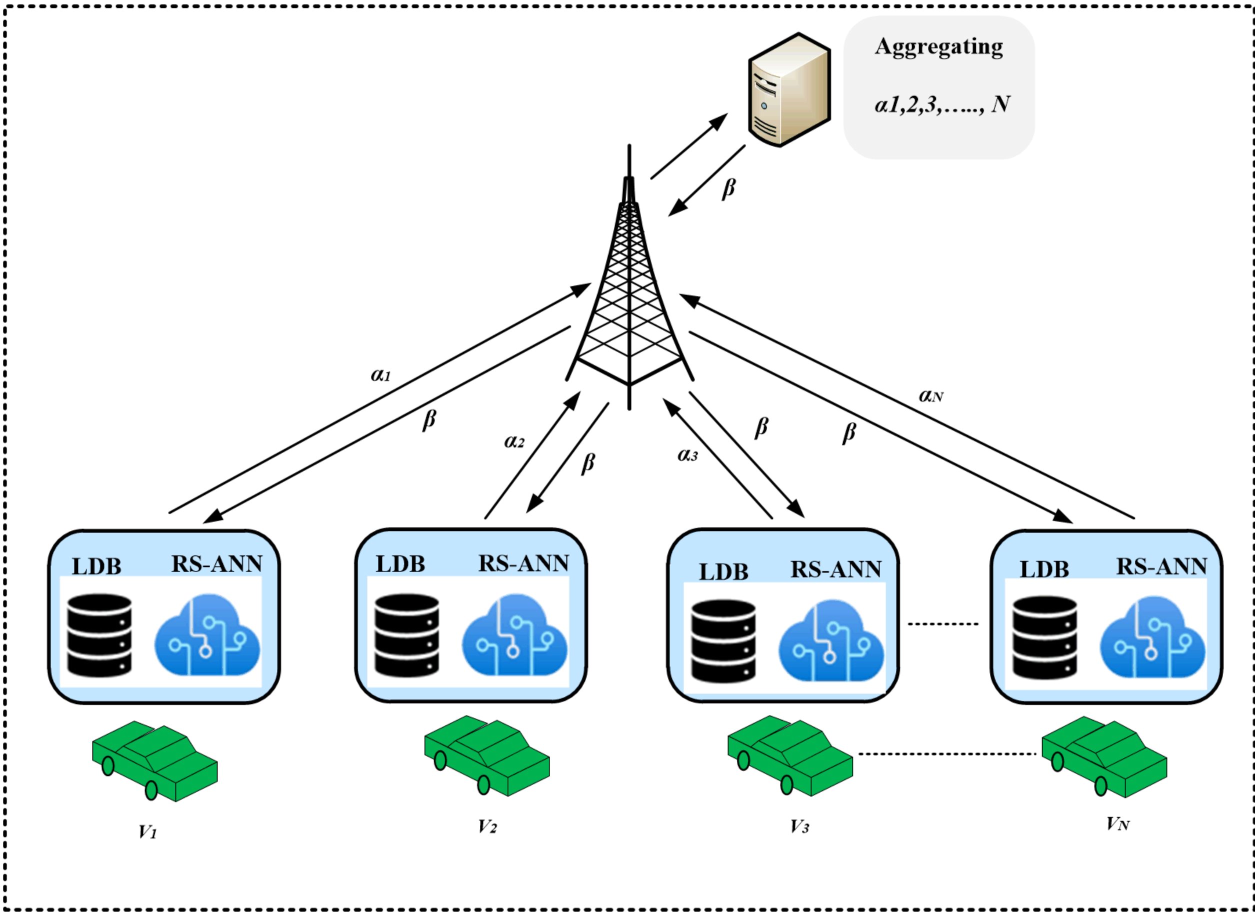

FIGURE 4. Proposed Vehicular Federated Learning.

QoS values, and VN_3 for low QoS values), as illustrated in (6). Each VN operates independently using the allocated resources (bandwidth (B), number of antennas (A), and bit rate (R)). Moreover, each gNB allocates computing resources (CPU (C) and memory (M)) according to the need to maximize the spectrum and energy efficiency. Scaling the computing resources of the gNB will significantly improve the processing speed of critical tasks, such as ESM transmission, as illustrated in this paper in Algorithm 3. As per the proposed framework, the virtualization and adaptive beamforming configurations are completely handled by the SDN controller, as shown in Fig. 5 and Fig. 6. Algorithm 2 illustrates the process of Fig. 5 and Fig. 6 in steps 3–24. Fig. 5 shows that the SDN controller applies the right configuration for each task. The dynamic allocation of network resources (gNB_{nr_i}) and computing resources (gNB_{cr_i}) can be provided. Fig. 6 shows that the SDN controller enables the optimal beamforming strategy to prioritize ESMs by shifting and amplifying the 5G MIMO antennas toward the DV. Steps 3–24 in Algorithm 2 show how the SDN allocates B and M based on RD; allocates R based on VS; and allocates A and C based on the QoS value (calculated in (5)) to handle each ESM independently, thereby improving the spectral efficiency and SINR.

$$\begin{aligned} &\text{Th1 (High QoS values)} : 0.7 < QoS \leq 1.06 \\ &\text{Th2 (Medium QoS values)} : 0.3 < QoS \leq 0.7 \\ &\text{Th3 (Low QoS values)} : QoS \leq 0.3 \end{aligned} \tag{6}$$

3) SDN-ENABLED ROUTING

The SDN controller traces the most optimal route (the best gNB) to send the ESM to the destination with less packet loss and delay.

On the basis of these objectives, the SDN controller sends OpenFlow control messages to the switches (gNBs and routers) to deliver the ESM as reliably as possible, enabling the vehicle to take appropriate action (e.g., stopping and changing direction) based on the SDN control messages received.

In the proposed framework, we initially assume that all the gNBs have the same signal that is transmitted to the vehicles over the corresponding transmission range of each gNB. Under standard circumstances, we assign the total network,

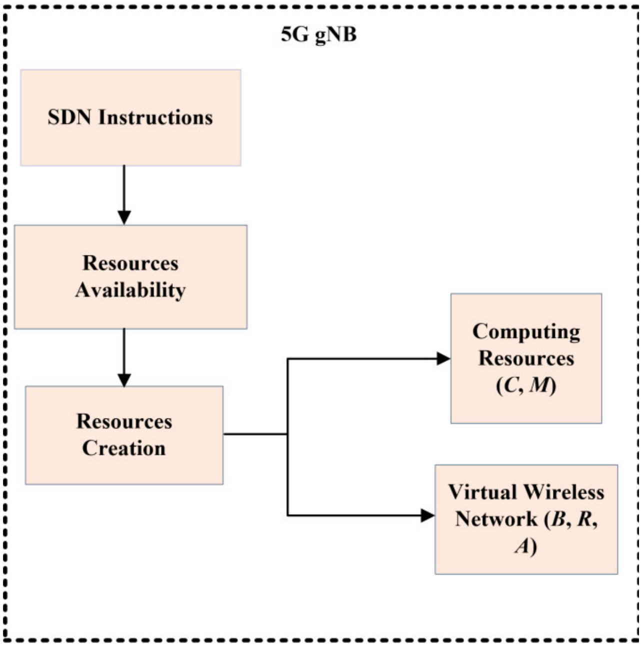

FIGURE 5. Dynamic allocation of 5G resources by SDN.

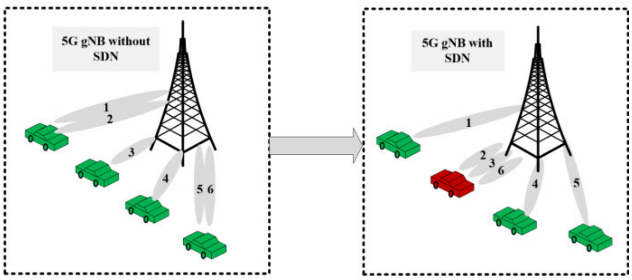

FIGURE 6. Adaptive beamforming by SDN.

total complexity, and connectivity of any gNB as follows:

$$gNB_{total\_net} = MAX.B + MAX.R + MAX.M \quad (7)$$

$$gNB_{total\_comp} = MAX.A + MAX.C + MAX.M \quad (8)$$

$$gNB_{connectivity} = MAX.B + MAX.R + MAX.A \quad (9)$$

We define the priority of the ESM using (10), which indicates that the gNB provides faster processing of ESMs with higher priority:

$$ESM\_Priority = \frac{QoS}{1.06} \quad (10)$$

Algorithm 3 explains how the gNB schedules the ESMs based on their priorities and configures its resources (gNB_{nr_i} and gNB_{cr_i}) based on the OpenFlow control message received from the SDN.

VI. PERFORMANCE EVALUATION

A. SIMULATION SCENARIOS

We consider two scenarios to simulate the proposed VFL algorithm (Algorithm 1) in our SDNCA framework. Scenario 1 has 100 vehicles with one ES, whereas Scenario 2 has 400 vehicles with four ESs. Python programming language is utilized to simulate the proposed VFL (Pytorch for the machine learning library). We generate the training and testing datasets as random integer values for each feature, as listed in Table 2, to feed the RS-ANN model implemented in the vehicles. The RS-ANN model consists of four fully connected layers with 32, 64, and 32 neurons in three hidden layers. Rectified linear units (ReLUs) are used as the activation functions of the three fully connected layers. The RS-ANN model is trained for 1000 epochs with cross-entropy loss and an Adam optimizer with a learning rate of 0.0001.

Network Simulator (NS3) is used to simulate 5G technology for vehicles by utilizing the MAC protocol, Orthogonal Frequency Division Multiple Access (OFDMA). Then, we simulate the SDNCA framework (Fig. 3) in a scenario of three gNBs, 100 vehicles, and one SDN controller.

Algorithm 2 Proposed Algorithm for SDN Objectives

Input: SV, DV, RS, VS, RD, defined tuple, 5G resources (gNB_{nr_i} and gNB_{cr_i})
Output: QoS, allocation of (gNB_{nr_i} and gNB_{cr_i}) for VN_1, VN_2, and VN_3, the selected route (SR), VS

1: Initialization: $B = 0, M = 0, R = 0, A = 0, C = 0$, $dest\_path \leftarrow \emptyset$
2: Calculate $QoS \leftarrow \frac{RS+VS}{RD}$
3: 5G resources ← set gNB_{nr_i} and gNB_{cr_i} based on QoS value
4: **for** each gNB **do:**
5: in each VN **do:**
6: **if** RD is in the range of a far distance
7: assign B ← highest value of B
8: assign M ← highest value of M
9: **elif** RD is in the range of a medium distance
10: assign B ← medium value of B
11: assign M ← medium value of M
12: **else**
13: assign B ← lowest value of B
14: assign M ← lowest value of M
15: **end**
16: **if** VS is high
17: assign R ← highest value of R
18: **elif** VS is medium
19: assign R ← medium value of R
20: **else**
21: assign R ← lowest value of R
22: **end**
23: assign A, assign C
24: **end for**
25: Possible Routes ← compute routes between SV and DV
26: SR ← choose the best route from the Possible Routes
27: Send OpenFlow control message (QoS, 5G resources, SR, VS)

Algorithm 3 Proposed Algorithm at the Selected gNB for Scheduling ESMs and Configuring ($\boldsymbol{gNB_{nr_i}}$ and $\boldsymbol{gNB_{cr_i}}$)

Input: QoS, 5G resources, SR, VS
Output: scheduling of ESMs, configuring of gNB_{nr_i} and gNB_{cr_i}
1: Initialization: $B_i = 50$MHz, $R_i = 500$Mbps, $A_i = 1$, $C_i = 1$, $M_i = 256$MB, $ESM\_Priority = 100$, $net\_overhead = 0$, $TR_i = 100$, $comp\_cost = 0$
2: At the selected gNB, after receiving the OpenFlow control message from SDN **do:**
3: Calculate $ESM\_Priority$ by (10) for scheduling, **then**
4: **if** $B > B_i$
5: $net\_overhead \leftarrow net\_overhead + (B - B_i)$
6: assign $B_i \leftarrow B$
7: $TR_1 \leftarrow TR_i - 1$
8: **else**
9: assign $B_i \leftarrow B$
10: **end**
11: **if** $R > R_i$
12: $net\_overhead \leftarrow net\_overhead + (R - R_i)$
13: assign $R_i \leftarrow R$
14: **else**
15: assign $R_i \leftarrow R$
16: **end**
17: **if** $A > A_i$
18: $comp\_cost \leftarrow comp\_cost + (A - A_i)$
19: assign $A_i \leftarrow A$
20: $TR_2 \leftarrow TR_1 - 1$
21: **else**
22: assign $A_i \leftarrow A$
23: **end**
24: **if** $C > C_i$
25: $comp\_cost \leftarrow comp\_cost + (C - C_i)$
26: assign $C_i \leftarrow C$
27: **else**
28: assign $C_i \leftarrow C$
29: **end**
30: **if** $M > M_i$
31: $net\_overhead \leftarrow net\_overhead + (M - M_i)$
32: $comp\_cost \leftarrow comp\_cost + (M - M_i)$
33: assign $M_i \leftarrow M$
34: **else**
35: assign $M_i \leftarrow M$
36: **end**

The gNBs are connected through an SDN switch. An OpenFlow v1.0 OpenVSwitch virtual switch is used. The switch is managed by a Ryu SDN controller, which is written in Python. Table 3 displays the simulated parameters of SDNCA. Thus, the effectiveness of SDNCA is evaluated based on the following validation metrics by varying the density and velocity of the vehicles:

1) Network Overhead (NO) and Computational Complexity (CC): We define network overhead and computational complexity percentages in terms of consuming network resources (gNB_{nr_i}) and computing resources (gNB_{cr_i}). Network overhead represents the percentage of the consumption (B, R, and M) of the total network (MAX.B, MAX.R, and MAX.M), whereas computational complexity represents the percentage of the consumption (A, C, and M) of the total complexity (MAX.A, MAX.C, and MAX.M) of the selected gNB that forwards the ESM to the DV. These metrics are computed by the following equations:

TABLE 3. Simulation parameters.

PARAMETER	VALUE
MAC protocol	OFDMA
Transport protocol	TCP
ESM packet size	1024 bytes
Range of VS values (km/hr)	Low speed: 50-80 Medium speed: 80-100 High speed: 100-150
Number of the vehicles	100, 400 in VFL 100 in SDNCA framework
Environment	Highways
5G Base Stations (gNB_{ci})	3
SDN Controller	1
Simulation time	VFL: 14820 s SDNCA framework: 2400 s
Batch size	32
Defined gNB_{nr_i} and gNB_{cr_i} with maximum values	MAX.B = 10000MHz, MAX.A= 10, MAX.M = 4096MB, MAX.C = 32, MAX.R = 10000Mbps
Used gNB_{nr_i} and gNB_{cr_i} in each VN	VN_1 (B: 80MHz, 60MHz, 50MHz) (M: 1GB, 768MB, 512MB) (R: 1Gbps, 750Mbps, 500Mbps) (A: 3, C: 2) VN_2 (B: 60MHz, 50MHz, 50MHz) (M: 768MB, 512MB, 256MB) (R: 750Mbps, 650Mbps, 500Mbps (A: 2, C: 2) VN_3 (B: 60MHz, 50MHz, 50MHz) (M: 512MB, 256MB, 256MB) (R: 650Mbps, 550Mbps, 500Mbps) (A: 1, C: 1)
Critical value of RS	≥ 5
Range of RD values (m)	Close distance: 150-400 Medium distance: 400-700 Far distance: 700-1000

$$NO\_Percentage = \frac{net\_overhead}{gNB_{total\_net}} \tag{11}$$

where net_overhead is the network overhead, which is calculated in steps (5, 12, and 31, respectively) in Algorithm 3. Then, the network overhead (NO) at a given time is calculated by adding (NO_Percentage) to its current value

(NO_Current) as follows:

$$NO = NO\_Current + NO\_Percentage \quad (12)$$

$$CC\_Percentage = \frac{comp\_cost}{gNB_{total\_comp}} \quad (13)$$

where comp_cost is the complexity cost, which is calculated in steps (18, 25, and 32, respectively) in Algorithm 3. Then, the computational complexity (CC) at a given time is calculated by adding (CC_Percentage) to its current value (CC_Current) as follows:

$$CC = CC\_Current + C\_Percentage \quad (14)$$

2) Collision Rate (CR) of ESMs: We define the packet collision rate as the number of data packet collisions occurring in a network over a specified period. This metric is computed as the ratio of the number of collisions (N_c) with respect to the number of packets received by gNB (NP_{gNB}) as follows:

$$CR = \frac{N_c}{NP_{gNB}} \quad (15)$$

3) End-to-End (E2E) Delay: This metric is defined as the difference between the time at which the source (SV) transmits the ESM packet to the SDN controller (t_{tESM}) and the time at which the receiver (DV) receives the ESM packet (t_{rESM}). It can be measured as follows:

$$E2EDelay = t_{tESM} - t_{rESM} \quad (16)$$

4) Packet (ESM) Transmission Reliability (TR): This metric evaluates network connectivity and its ability to successfully deliver ESMs from the SV to the DV without errors, losses, or delays. This metric is affected by increasing the network overhead in terms of consuming B (as calculated in step 7 in Algorithm 3), increasing the computational complexity in terms of consuming A (as calculated in step 20 in Algorithm 3), and increasing the collision rate, respectively. The transmission reliability can be expressed mathematically as follows:

$$TR = TR_2 - CR \quad (17)$$

B. RESULTS ANALYSIS AND DISCUSSION

The evaluation results of the real-time simulation of the proposed VFL algorithm are shown in Figs. 7–9. Fig. 7 (a) shows the training and test accuracies in Scenario 1. In this scenario, we achieve 95.60% training accuracy and 98.00% test accuracy at epoch 346. Fig. 7 (b) shows the training and test accuracies in Scenario 2. This scenario results in 95.30% training accuracy and 96.00% test accuracy at the same epoch. Given an increase in the number of training vehicles, these values reach 98.10% training accuracy and 99.00% test accuracy at epoch 1000 in Fig. 7 (a), whereas training accuracy is 97.90% and test accuracy is 96.00% at epoch 1000 in Fig. 7 (b).

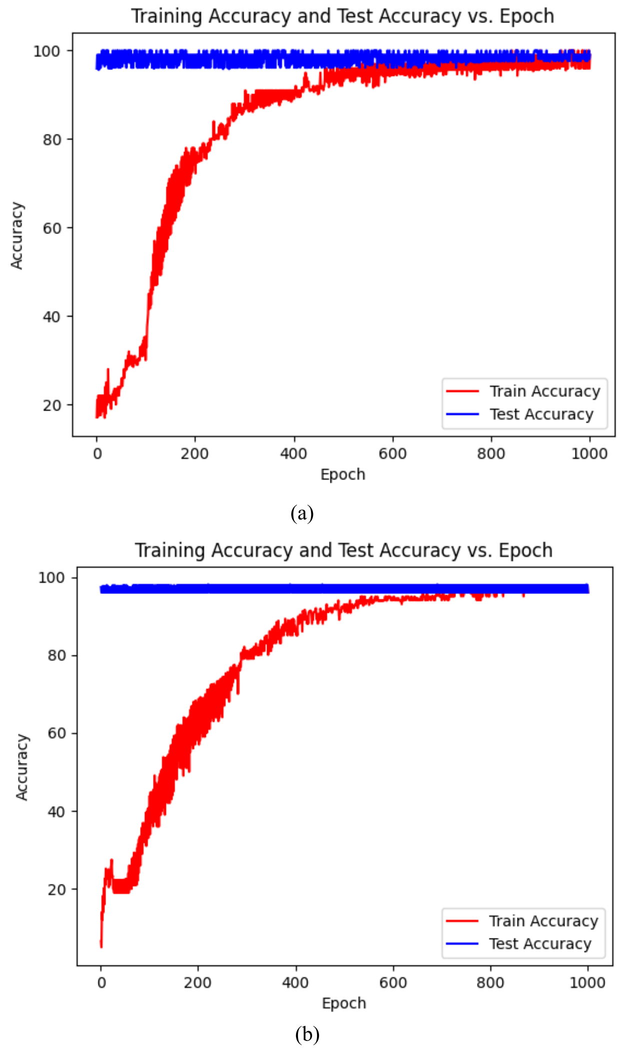

FIGURE 7. Training and test accuracy for 100 vehicles (b). Training and test accuracy for 400 vehicles.

Overall, high average accuracy values are obtained in Fig. 7 (a) and Fig. 7 (b) because we design an accurate RS-ANN training model, in addition to the participation of all vehicles in the training process, which results in higher accuracy values. Thus, the proposed VFL algorithm yielded identical results, except for a small gap in its convergence speed between the two scenarios. Using the ES that has the capacity of four ESs (each 100 vehicles handled by one ES) that distribute the load in Scenario 2 constitutes a key factor for obtaining these identical values.

Fig. 8 (a) and Fig. 8 (b) demonstrate the training and test losses for the RS-ANN model, which is a regression network outputting the RS value of V_i in Scenario 1 and Scenario 2, respectively. The train and test losses significantly drop from more than 2.0 to 0.0760 train loss and 0.0493 test loss (Fig. 8 (a)), and to 0.0657 train loss and 0.0727 test loss (Fig. 8 (b)). Fig. 8 (a) and Fig. 8 (b) show smooth curves without any fluctuations and with little differences between

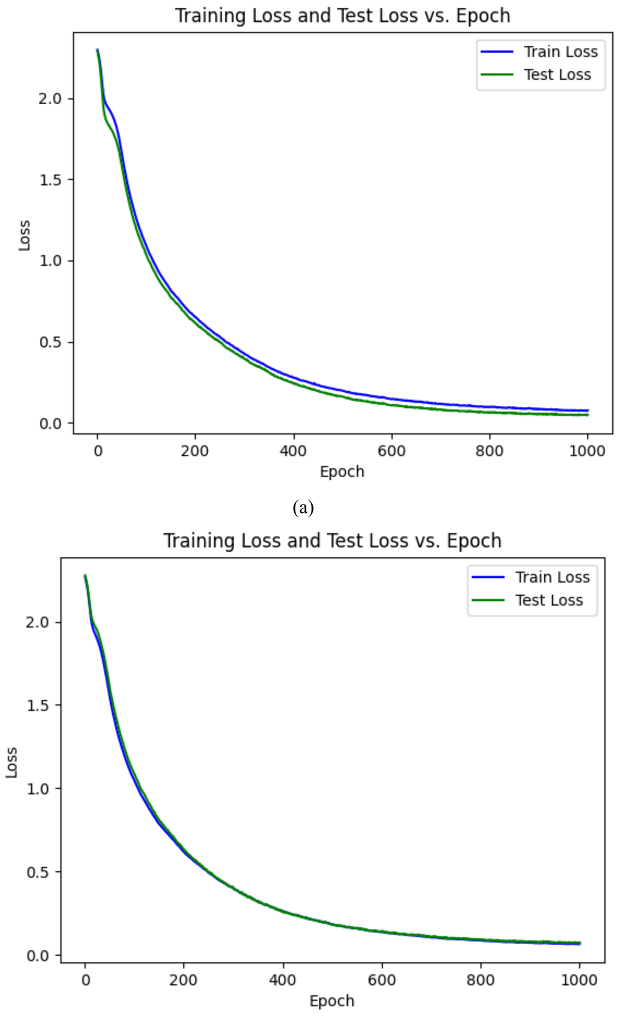

FIGURE 8. **Training and test losses for 100 vehicles (b). Training and test losses for 400 vehicles.**

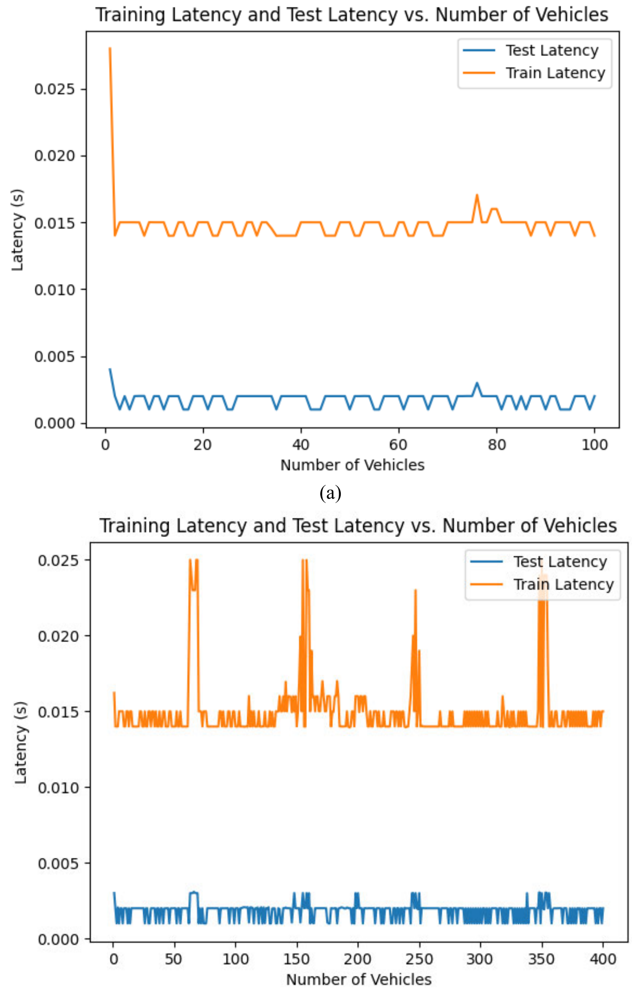

FIGURE 9. **Training and test latencies with different numbers of vehicles (b). Training and test latencies with different numbers of vehicles.**

them in both scenarios. This indicates that the proposed VFL algorithm is stable due to the load balancing of the data packets and because we do not have major losses in the entire system.

The training and test latencies are critical parameters that should be investigated in the federated learning process as they affect the transmission latency of ESMs in any system model. We measure these parameters, as shown in Fig. 9 (a) for Scenario 1 and Fig. 9 (b) for Scenario 2, with accurate and desirable values. Initially, the training latency is more than 0.025 s and then decreases to approximately 0.0150 s in Fig. 9 (a); however, the value of the test latency remains constant at 0.002 s in Fig. 9 (a). As shown in Fig. 9 (b), the training latency is 0.015 s, fluctuations are observed at some values (e.g., the training latency is 0.025 s when the training vehicles are more than 50). These fluctuations are due to the training process, and we achieve the same test latency value shown in Fig. 9 (b). Technically, the test latency should be lower than the training latency, which our results scrutinize.

Fig. 9 (a) and Fig. 9 (b) also show that increasing the number of vehicles does not affect the training and test latencies, which makes our system model more adaptable to IoV as the number of vehicles is increased or decreased in a specific area at a certain time.

The proposed SDNCA framework is simulated by considering vehicle density and vehicle speed and compared with [74] for one common point, that is, SDNCA and [74] simulated 5G technology for IoV. The novelty of the SDNCA framework compared with [74] relies on the following main facts: First, we consider vehicle speed in the SDNCA framework, but its implementations were not considered in [74], which is a drawback of the study. Second, we implement federated learning in the SDNCA framework in Section V-A, with efficient results shown in Figs. 7–9, which were not implemented in [74]. Third, we perform a real-time simulation of the SDN core routers at the backbone layer in Section V-B, along with ES execution at the edge layer to handle the overall network load. However, the topology in [74] requires more than one SDN controller and one core router

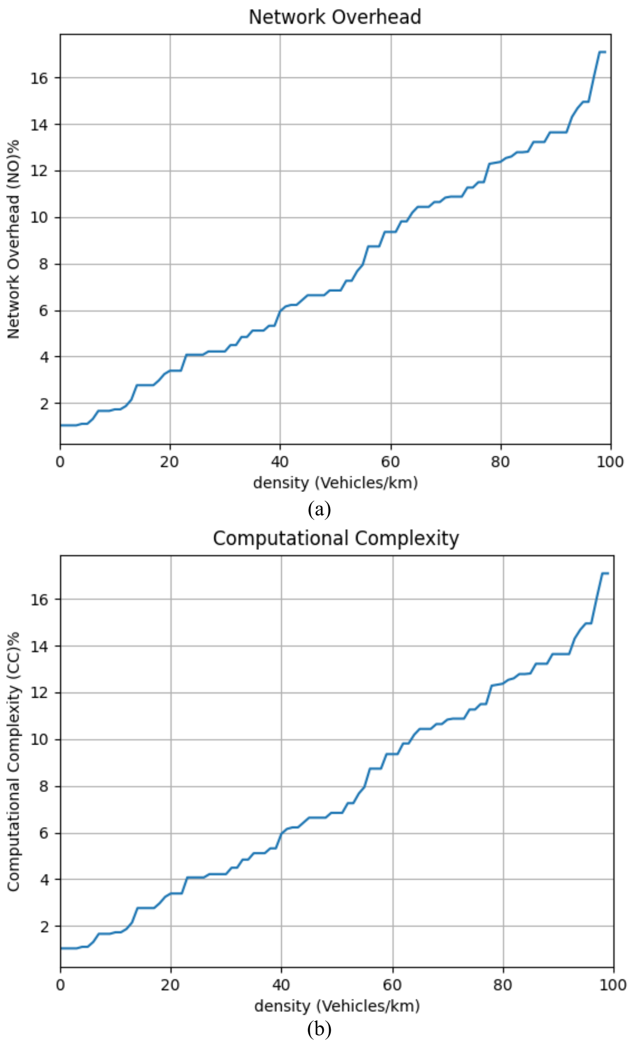

FIGURE 10. **(a). Evaluation of Network Overhead (b). Evaluation of Computational Complexity.**

to balance the load of 800 vehicles, and it does not mention the technical aspects of the core layer. Thus, technically, the system model in [74] has jitters, delays, and damage at a certain stage.

Controlling the network overhead and computational complexity is crucial for any real-time simulation. Fig. 10 (a) and Fig. 10 (b) show the optimized network results of 17% when N = 100 vehicles/km in the SDNCA framework, due to the intelligent utilization of gNB_{nr_i} and gNB_{cr_i}. By contrast, the study in [74] obtained less network overhead and computational complexity than the SDNCA framework when N = 100 vehicles/km, and when N = 800 vehicles/km in [74], the network overhead is 21% and the computational complexity is 19.8%. Hence, the study in [74] did not simulate the federated learning and core layer because the real-time simulation for more network devices, core routers, and ESs will increase the network overhead and computational complexity by more than 21% and 19.8%, respectively, thereby achieving 17% in the SDNCA framework for the real-time simulation of 100 vehicles/km, which is considered an ideal value.

The SDNCA framework possesses a 0% collision rate for ESMs, as shown in Fig. 11 (a) and Fig. 11 (b). With increasing vehicle density and vehicle speed, the collision rate remains at 0, which denotes the ideality of SDNCA and its proper configuration to transmit ESMs based on their priorities (as calculated in (10)), thereby realizing the avoidance of vehicle collisions in 5G environment. The SDNCA framework outperforms the method in [74], with collision rates of approximately 4% and 9% at N = 100 vehicles/km implemented in two different scenarios.

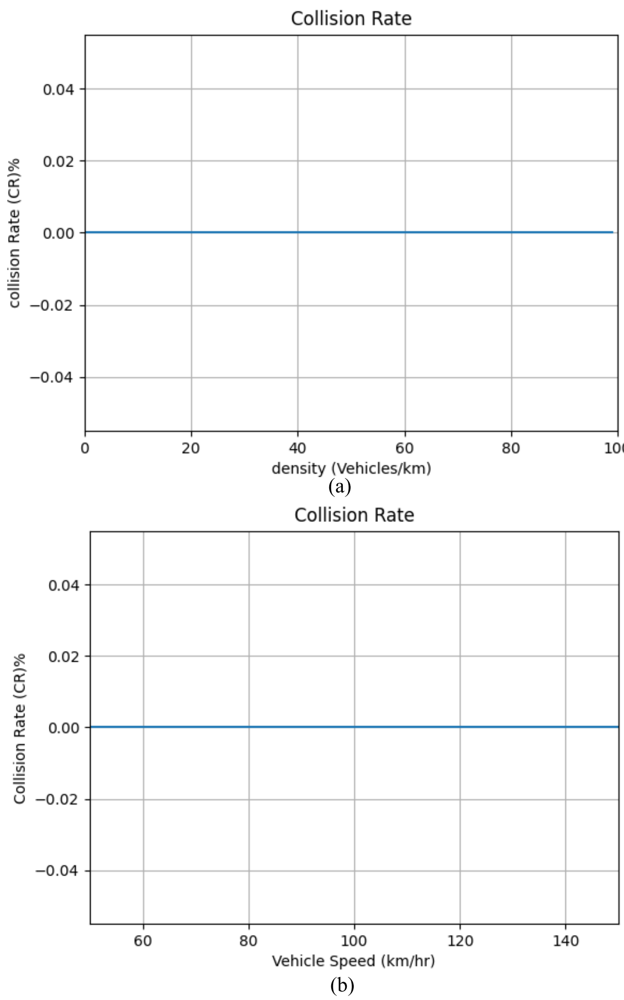

FIGURE 11. **Evaluation of Collision Rate vs. vehicle density (b). Evaluation of Collision Rate vs. vehicle speed.**

In contrast with [74], our analysis of the average end-to-end delay of the SDNCA framework, which is depicted in Fig. 12 (a) and Fig. 12 (b), reveals that the end-to-end delay in the SDNCA framework is 18 ms at N = 100 vehicles/km, which is approximately equal to the value obtained in [74] for more than 300 vehicles/km. The lower end-to-end delay values in the SDNCA framework, when vehicle density and speeds increase, are due to the utilization of high computing

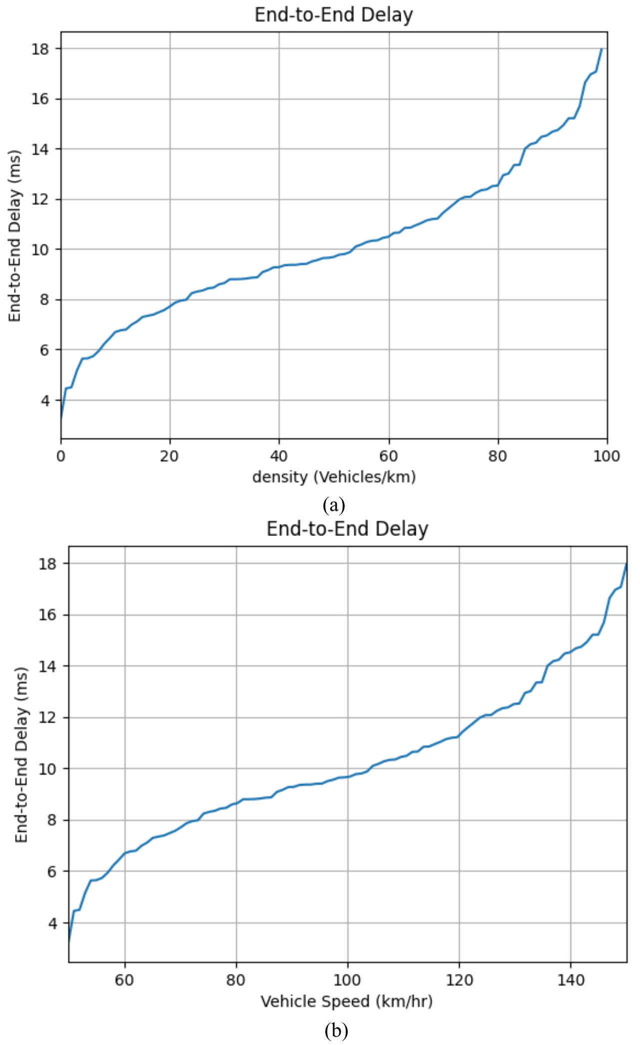

FIGURE 12. **(a). Evaluation of End-to-End delay vs. vehicle density (b). Evaluation of End-to-End delay vs. vehicle speed.**

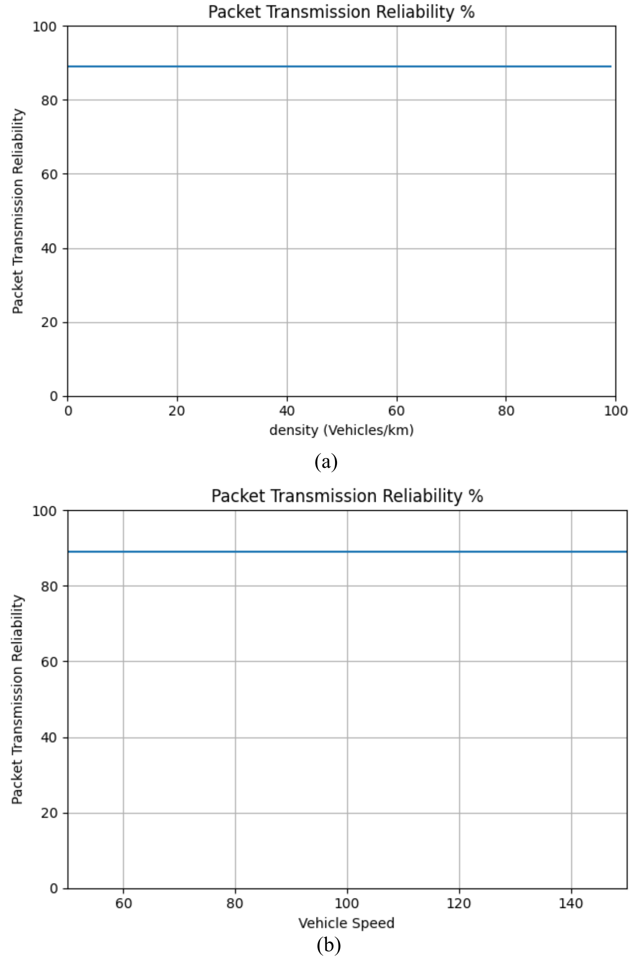

FIGURE 13. **(a). Evaluation of Packet (ESM) Transmission Reliability vs. vehicle density (b). Evaluation of Packet (ESM) Transmission Reliability vs. vehicle speed.**

resources to transmit ESMs faster based on their priorities (as calculated in (10)), which are considered ideal values for simulating the core and edge layers compared with [74].

The results shown in Fig. 13 (a) and Fig. 13 (b) indicate that the SDNCA framework can provide high reliability of ESM transmission because it has a constant value of 89%–90% as the vehicle density and vehicle speed increase. In comparison, [74] shows superior values at N = 100 vehicles/km, but its reliability decreases as the vehicle density increases. Achieving 0% collision rates in SDNCA leads to a constant value of 89%–90%.

We can conclude two main points from Figs. 10–13 in the SDNCA framework that should be scrutinized in real-time simulation. First, we achieve the same values of network overhead and computational complexity because these metrics are complementary and directly proportional to each other. Second, Figs. 11–13 have the same values of collision rates, end-to-end delay, ESM transmission reliability when increasing the vehicle density, and vehicle speed. These results show the effectiveness of the SDNCA framework, which handles the ESMs simultaneously (Algorithms 1–3) to avoid vehicle collision compared with the system model in [74], which cannot consider an efficient system to cater to the critical requirements of ESM transmission in the network due to the reasons mentioned previously in this section.

VII. CONCLUSION AND FUTURE WORK

The SDN can be a prominent technology for 5G-IoV communications, particularly for ESM transmission. This paper proposes an SDNCA framework to efficiently transmit ESMs from the SV to the DV and avoid vehicle collisions. The core contribution of the SDNCA is optimizing the network communication of ESMs to vehicles in terms of QoS. The SDNCA implements VFL using Algorithm 1, which provides two important points. First, the proposed VFL is unaffected by the number of vehicles in terms of training accuracy, test accuracy, train loss, test loss, training latency, and test latency. Second, desirable results are obtained when all vehicles (not some vehicles) participate in the training process. Therefore, the system model is stable and adaptable to the vehicular networks for any number of vehicles because it achieves load balancing according to the ESs, backbone routers, and gNBs that we have used.

Algorithm 2 is applied to calculate the QoS, allocate the 5G network and computing resources ($\boldsymbol{gNB_{nr_i}}$ and $\boldsymbol{gNB_{cr_i}}$), and select the best route (best gNB) from the SV to the DV. Algorithm 3 then schedules the ESMs based on their priorities and configures the $\boldsymbol{gNB_{nr_i}}$ and $\boldsymbol{gNB_{cr_i}}$ of the selected gNB based on the SDN OpenFlow control message. Algorithms 2 and 3 handle each ESM independently to achieve improved V2V communication.

Finally, the SDNCA performance is validated through five evaluation metrics, namely, Network Overhead (NO), Computational Complexity (CC), Collision Rate (CR), End-to-End (E2E) Delay, and Packet (ESM) Transmission Reliability (TR), and compared with [74]. The SDNCA framework achieves a 0% collision rate, which is an ideal value that can fulfill the stringent requirements for ESM transmission in 5G-IoV environment.

In the future, we suggest designing a more complicated network using the same proposed SDNCA framework but on an extremely large scale. Specifically, we intend to simulate a larger network consisting of 5G or 6G with 1000 vehicles, two SDN controllers, and 20 backbone routers to enhance coverage.

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