

Adaptive SDN-Assisted Traffic Signal Control for Road Traffic Congestion Mitigation in VANETs

Augastiny Ramesh

sweetaugas@pondiuni.ac.in

Pondicherry University

Samundiswary Punniakodi

Pondicherry University

Research Article

Keywords: VANET, SDN, Adaptive Traffic Signal Control, V2I Communication, Traffic Congestion Mitigation, Round-Robin Scheduling

Posted Date: October 23rd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10979316/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Adaptive SDN-Assisted Traffic Signal Control for Road Traffic Congestion Mitigation in VANETs

Augastiny Ramesh

Department of Electronics Engineering,
Pondicherry University
Pondicherry, India
sweetaugas@pondiuni.ac.in

Samundiswary Punniakodi

Department of Electronics Engineering,
Pondicherry University
Pondicherry, India
sam.dee@pondiuni.ac.in

Abstract—Road traffic congestion at urban intersections leads to increased travel delays, fuel consumption, and degraded communication performance in Vehicular Ad Hoc Networks (VANETs). This paper proposes an adaptive SDN-assisted traffic signal control framework that leverages Software-Defined Networking (SDN) to prioritize the most congested road based on real-time traffic conditions, including queue length, lane density, and vehicle arrivals. The proposed framework is implemented using the NS-3 network simulator integrated with SUMO mobility. Simulation results demonstrate that the proposed framework significantly reduces queue length, waiting time, and fuel consumption while increasing cumulative vehicle discharge. Furthermore, it achieves higher packet delivery ratio (PDR), improved throughput, and lower end-to-end delay than conventional traffic signal control. These results demonstrate that the proposed framework provides an effective solution for intelligent road traffic congestion mitigation in VANETs.

Keywords— VANET, SDN, Adaptive Traffic Signal Control, V2I Communication, Traffic Congestion Mitigation, Round-Robin Scheduling.

I. INTRODUCTION

The rapid growth of urban vehicular traffic has intensified congestion at signalized intersections, leading to increased travel delay, queue formation, fuel consumption, and inefficient utilization of road capacity. Since traffic demand varies dynamically across intersection approaches, fixed-time signal control is often unable to respond effectively to changing traffic conditions. Consequently, adaptive traffic signal control has emerged as an important approach for improving intersection efficiency in intelligent transportation systems [1], [2].

The development of connected vehicles has enabled traffic control systems to obtain real-time information from vehicles through Vehicle-to-Infrastructure (V2I) communication. Roadside Units (RSUs) can collect vehicle information such as position, speed, and traffic presence, providing a more dynamic representation of traffic conditions at an intersection. Such information can be utilized to support adaptive signal decisions and improve traffic management under varying traffic densities [1]–[3], [5].

Software-Defined Networking (SDN) provides centralized and programmable control that can facilitate the aggregation and processing of traffic information from distributed roadside infrastructure. The integration of SDN with vehicular networks has been investigated for improving network management, routing, and traffic-related services [4]. However, the direct use of real-time V2I information within an SDN controller for traffic-demand-based signal³ phase prioritization at an individual intersection remains comparatively less explored.

To address this gap, this paper proposes an Adaptive SDN Traffic Signal Control algorithm for a four-way urban intersection.

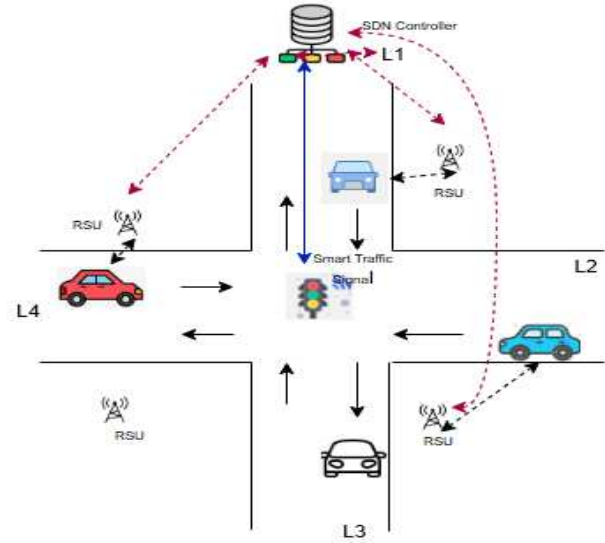


Fig. 1. Four-way intersection SDN- VANET Architecture

The proposed algorithm collects V2I beacon messages via RSUs and periodically evaluates the traffic demand across all incoming approaches as shown in Fig.1. The SDN controller identifies the approach with the highest demand and assigns priority to its corresponding signal phase. After serving the priority lane, the remaining approaches are served in a structured sequence using Round-Robin (RR) scheduling. The proposed framework is implemented using an integrated NS-3, SUMO, and Ryu SDN controller environment and evaluated under varying vehicle densities. Performance is assessed using key network metrics, including Packet Delivery Ratio (PDR), network throughput, and end-to-end delay.

The main contributions of this work are:

1. An SDN-assisted adaptive traffic signal control algorithm utilizing real-time V2I information to prioritize high-demand approaches while maintaining fair service across remaining lanes via Round-Robin scheduling.
2. An integrated NS-3/SUMO/Ryu simulation framework to evaluate SDN-VANET control mechanisms under dynamic vehicular densities.

A quantitative performance evaluation demonstrating the impact of adaptive signal control on key network

communication metrics (PDR, throughput, and end-to-end delay).

II. RELATED WORK

A. Adaptive Traffic Signal Control

Adaptive traffic signal control has been widely investigated to improve traffic flow at urban intersections by dynamically adjusting signal timing based on real-time traffic conditions. Li *et al.* [1] and Peng *et al.* [15] presented comprehensive reviews of adaptive traffic signal control techniques in connected vehicle environments, highlighting the importance of real-time traffic information and intelligent control strategies for improving intersection efficiency. Mo *et al.* [2] proposed CVLight, a decentralized deep reinforcement learning framework that optimizes traffic signal timing using connected vehicle information. Similarly, Shi *et al.* [16] and Yang *et al.* [17] employed deep reinforcement learning and multi-agent learning techniques to improve traffic signal performance under dynamic traffic conditions. Although these approaches significantly improve traffic efficiency, they require extensive training and computational resources. Tan and Yang [3] further introduced a privacy-preserving adaptive traffic signal control framework that maintains traffic efficiency while

protecting vehicle privacy. In addition, fog computing and connected vehicle technologies have been incorporated into adaptive signal control to reduce congestion and improve public transportation efficiency [5], [12]. Comprehensive surveys have also summarized optimization-based, learning-based, and intelligent traffic signal control methods while identifying challenges related to scalability, computational complexity, and deployment in large urban networks [6]

B. SDN-Based Vehicular Networks

Software-Defined Networking (SDN) has emerged as an effective solution for centralized control and efficient resource management in Vehicular Ad Hoc Networks (VANETs). Rajan *et al.* [4] demonstrated the effectiveness of adaptive SDN in improving communication performance in vehicular environments. Han *et al.* [7] proposed an SDN-based vehicular networking architecture that enhances routing flexibility and centralized network management, while Al-Heety *et al.* [11] and Mekki *et al.* [19] comprehensively reviewed SDN-VANET architectures, applications, and associated challenges. OpenFlow has further enabled programmable network management through centralized control [10], serving as the foundation for many SDN-enabled vehicular applications. Furthermore, Balta *et al.* [14] proposed intelligent traffic signal optimization using

TABLE I. COMPARISON OF EXISTING ADAPTIVE TRAFFIC SIGNAL CONTROL APPROACHES

Ref.	Method/Approach	Technologies Used	Key Contribution	Limitation
[1]	Review of adaptive traffic signal control	Connected Vehicles (CV), Intelligent Transportation Systems (ITS)	Comprehensive survey of adaptive traffic signal control techniques	Review paper; no implementation or new control algorithm
[2]	CVLight	CV, Deep Reinforcement Learning (DRL)	Decentralized adaptive traffic signal control using connected vehicle data	High computational complexity; does not employ SDN
[3]	Privacy-preserving adaptive traffic signal control	Connected Vehicles (CV), privacy-preserving protocols	Enhances privacy while maintaining adaptive signal control	Does not consider SDN-based centralized traffic management
[4]	Adaptive SDN traffic management	SDN, VANETs	Centralized network management and improved communication efficiency	Focuses on networking rather than traffic signal phase control
[5]	Connected vehicle-supported adaptive traffic control	V2I, CV	Uses real-time vehicle information for adaptive signal timing	Does not integrate SDN architecture
[6]	Multi-agent reinforcement learning for traffic signal control	Reinforcement Learning (RL), Intelligent Transportation Systems (ITS)	Optimizes signal timing under varying traffic demand	Requires extensive training and computational resources
[7]	SDN-enabled VANET architecture	SDN, OpenFlow protocol	Improves routing flexibility and centralized control	Does not address adaptive intersection signal control
[8]	RSU-assisted traffic management	RSUs, V2I	Real-time vehicle monitoring for intelligent transportation	Focuses on traffic monitoring rather than signal prioritization
[9]	Intelligent intersection management	V2I, Edge Computing	Reduces vehicle delay using edge-assisted decision making	Limited integration with SDN controllers
[10]	Hybrid SDN-VANET framework	SDN, VANETs, Internet of Vehicles (IoV)	Enhances communication reliability and resource management	Does not prioritize signal phases using traffic demand
[14]	Fuzzy decision-tree signal optimization	SDN, VANET, Fuzzy Logic	Optimizes urban traffic signal timing via SDN architecture	Focuses on static decision trees; high computational overhead

a fuzzy decision-tree model. These studies demonstrate the effectiveness of SDN in vehicular networking; however, they primarily emphasize communication management rather than adaptive signal phase prioritization.

C. Connected Vehicle Communication

Recent advances in connected vehicle communication have enabled real-time information exchange between vehicles and roadside infrastructure through Vehicle-to-Infrastructure (V2I) communication. Abboud et al. [8] reviewed the integration of Dedicated Short-Range Communications (DSRC) and cellular networks for V2X communication, while Gerla et al. [9] introduced the Internet of Vehicles (IoV) paradigm for intelligent transportation systems. Maadi et al. [20] demonstrated the effectiveness of reinforcement learning with connected and automated vehicles for adaptive traffic signal control. In addition, Gillani et al. [21] surveyed data collection protocols in VANETs, emphasizing efficient dissemination of real-time vehicular information for intelligent transportation applications.

D. Research Gap

Although previous studies have demonstrated significant improvements in adaptive traffic signal control, SDN-enabled vehicular networking, and connected vehicle communication, several limitations remain. Most adaptive traffic signal control approaches rely on computationally intensive optimization or reinforcement learning algorithms without exploiting SDN for centralized traffic control. Existing SDN-based vehicular network studies primarily focus on communication performance, routing, congestion control, and resource management rather than adaptive traffic signal phase prioritization. Furthermore, limited attention has been given to integrating real-time Vehicle-to-Infrastructure (V2I) beacon information with an SDN controller for traffic-demand-based signal phase prioritization while simultaneously ensuring fair service to the remaining approaches. To address these limitations, this paper proposes an Adaptive SDN Traffic Signal Control framework that combines real-time V2I information, SDN-based centralized control, and Round-Robin scheduling to improve both traffic management and communication performance.

III. PROPOSED ALGORITHM

A. Proposed Framework

The proposed framework considers a software-defined vehicular network (SDVN)-enabled four-way signalized intersection consisting of four incoming lanes, denoted by L_1, L_2, L_3, L_4 . Each approach is monitored by a Roadside Unit (RSU), which continuously receives Vehicle-to-Infrastructure (V2I) beacon messages broadcast by vehicles within its communication range. Instead of forwarding every beacon packet to the centralized controller, each RSU performs local traffic aggregation to reduce communication overhead.

At every phase decision window, T_{slot} , the RSU computes a compact lane-level traffic summary for each incoming lane. The summary consists of the Lane Queue Count (Q_i) and the Average Lane Speed $V_{avg,i}$, which together represent the instantaneous traffic conditions of the corresponding lane. The summarized information is encapsulated in an OpenFlow **Packet-In** message and transmitted to the centralized SDN controller.

Upon receiving the lane summaries from all RSUs, the SDN controller constructs a global view of the intersection and computes the dynamic lane density ρ_i for each lane.

$$\rho_i = \frac{Q_i}{V_{avg,i} + \epsilon} \quad (1)$$

ϵ is a small positive constant ($\epsilon = 10^{-3}$) added to prevent division by zero when traffic is completely stationary.

Based on the computed density values, the controller identifies the target lane (L^*) experiencing the highest traffic demand:

$$L^* = \arg \max_{i \in \{1,2,3,4\}} \rho_i \quad (2)$$

where $\rho_{max} = \max\{\rho_1, \rho_2, \rho_3, \rho_4\}$

Then the controller allocates green signal priority to the corresponding traffic phase for the next decision interval. If two or more lanes exhibit identical or near-identical maximum density values, a Round-Robin (RR) mechanism is employed to ensure fairness and prevent lane starvation.

Finally, the SDN controller transmits an OpenFlow **Flow-Mod** message to the corresponding RSU or traffic signal controller to grant green signal priority to the selected lane for the next decision interval. This process is repeated every decision window T_{slot} , allowing the traffic signal controller to continuously adapt to changing traffic conditions while maintaining low communication overhead through lane-level traffic information aggregation.

B. Lane-Level Traffic Information

The Lane Queue Count (Q_i) represents the number of stopped or slow-moving vehicles in lane i . A vehicle is considered queued when its speed satisfies $v_k \leq v_{th}$, where $v_{th} = 5$ km/h. Thus,

$$Q_i = \sum_{k=1}^{N_i} I(v_k \leq v_{th}),$$

where N_i is the number of vehicles detected in lane i , and $I(v_k \leq v_{th})$ is an indicator function.

The Average Lane Speed is calculated from the instantaneous speeds of vehicles detected in lane i as

$$V_{avg,i} = \frac{1}{N_i} \sum_{k=1}^{N_i} v_k$$

The queue count provides a direct indication of congestion, while the average speed provides an additional indication of traffic-flow conditions. Therefore, the two metrics together provide the SDN controller with a compact representation of the traffic state of each lane.

C. Adaptive Phase Decision

To prioritize traffic demand dynamically while avoiding phase starvation, the SDN controller evaluates the lane density vector $\rho = [\rho_1, \rho_2, \rho_3, \rho_4]$ at the end of every decision window T_{slot} . The priority signal phase is determined through a two-step selection process:

1) Demand-Based Priority Assignment:

The controller selects the lane L^* exhibiting the maximum traffic density, according to Eq.(2). The signal phase corresponding to lane L^* is granted green light priority for the next decision interval.

2) Tie-Breaking and Starvation Prevention:

When two or more top-demanding lanes exhibit identical maximum density values (i.e., $\rho_i = \rho_j = \rho_{max}$), direct priority selection becomes ambiguous. In such instances, a Round-Robin (RR) scheduling rule is applied among the tied candidate lanes to ensure fair access and prevent starvation.

Once the phase decision is finalized, the controller issues an OpenFlow Flow-Mod message to update the signal controller state for the upcoming cycle, while the remaining non-priority lanes are scheduled sequentially according to the predefined phase order.

Algorithm 1: Adaptive SDN Traffic Signal Control

Input: Vehicle beacon messages from all vehicles, Decision window $T_{slot} = 50$ s, Threshold speed $v_{th} = 5$ km/h.

Output: Selected green traffic phase.

1. Initialize RSUs and SDN controller
2. **while** traffic system is active **do**
3. **for** each RSU **do**
4. Receive V2I beacon messages
5. Compute Queue Count Q_i
6. Compute Average Speed $V_{avg,i}$
7. Send $(Q_i, V_{avg,i})$ to SDN controller
8. **end for**
9. **for** each lane i **do**
10. Compute lane density ρ_i
11. **end for**
12. Find maximum density $\rho_{max} = \max(\rho_1, \rho_2, \rho_3, \rho_4)$
13. **if** multiple lanes have identical max density
 $(\rho_i = \rho_j = \rho_{max})$ **then**
14. Select target lane L^* via Round-Robin (RR)
15. **else**
16. Select target lane L^* with max density
17. **end if**
18. Transmit OpenFlow Flow-Mod message to activate green phase for lane L^*
19. Wait for decision interval T_{slot}
20. **end while**

D. Performance Evaluation Metrics

To evaluate the efficiency of this mechanism, multiple performance parameters are analyzed:

1) *Cumulative Vehicle Discharge Count* ($C_{dis}(t)$): Represents the total number of vehicles that successfully cross the intersection stop line during the simulation. A higher value indicates improved traffic flow and intersection efficiency.

$$C_{dis}(t) = \sum_{k=1}^{N_{total}} \mathbb{I}(T_{exit,k} \leq t)$$

2) *Average Vehicle Waiting Time* (W_{avg}): Measures the average time vehicles spend waiting at the intersection before passing through the signal. Lower waiting time indicates better traffic management.

$$W_{avg} = \frac{1}{N_{total}} \sum_{k=1}^{N_{total}} T_{wait,k}$$

3) *Packet Delivery Ratio (PDR)*: Measures the reliability of network communication by calculating the percentage of transmitted data packets that are successfully received.

$$PDR = \frac{\sum P_{received}}{\sum P_{transmitted}} \times 100\%$$

4) *Network Throughput (TH)*: Represents the average rate of successful data delivery over the network, measured in kilobits per second (kbps).

$$TH = \frac{\sum \text{Data Received (bits)}}{\Delta t \times 10^3}$$

5) *Average End-to-End Delay* (D_{E2E}): Represents the average time taken for data packets to travel from the source to the destination.

$$D_{E2E} = \frac{1}{P_{rec}} \sum_{p=1}^{P_{rec}} (T_{recv,p} - T_{sent,p})$$

where $T_{sent,p}$ and $T_{recv,p}$ denote the transmission and reception times of packet p , respectively.

IV. SIMULATION SETUP

The proposed algorithm was evaluated using an integrated simulation framework comprising SUMO (v1.15.0) for vehicular mobility, ns-3 for network communication, and the Ryu controller for centralized SDN management. A four-way urban intersection was modeled in SUMO, while ns-3 simulated IEEE 802.11p-based V2I communication between vehicles and Roadside Units (RSUs). The simulation parameters used in this study are summarized in Table II.

TABLE II. SIMULATION PARAMETER SETUP

Name of the Parameter	Value
Network Simulator	ns-3
Mobility Simulator	SUMO v1.15.0
SDN Controller	Ryu
Simulation Area	1500 m × 1500 m
Road Topology	Four-way urban intersection
Number of vehicles	10–250 vehicles
Simulation Time	300 s
Traffic Model	CBR over UDP
Packet Size	1024 Bytes
Beacon Interval	0.1 s (10 Hz)
MAC/PHY	IEEE 802.11p (WAVE / DSRC)
Propagation Model	Two-Ray Ground
Communication Range	250 m
Decision Window T_{slot}	50 s

V. RESULTS AND DISCUSSION

A. Queue Length Profile Over Time

As shown in Fig. 2, at $t = 50$ s, the queue length of Lane L1 decreases, whereas L2, L3, and L4, continue to increase, illustrating the operation of the proposed Adaptive SDN Traffic Signal Control algorithm, in which the prioritized lane is discharged while the remaining lanes temporarily accumulate vehicles during the red signal phase. At $t = 250$ s, L4 exceeds the queue spillover threshold due to a sudden increase in traffic demand. Under a traditional fixed-time signal, the next phase would have been allocated to L2 according to the predefined sequence, allowing congestion in L4 to worsen. In contrast, the Adaptive SDN Traffic Signal Control algorithm identifies L4 as the highest-demand lane and assigns it priority in the next decision window, resulting in a noticeable reduction in queue length and effectively mitigating congestion.

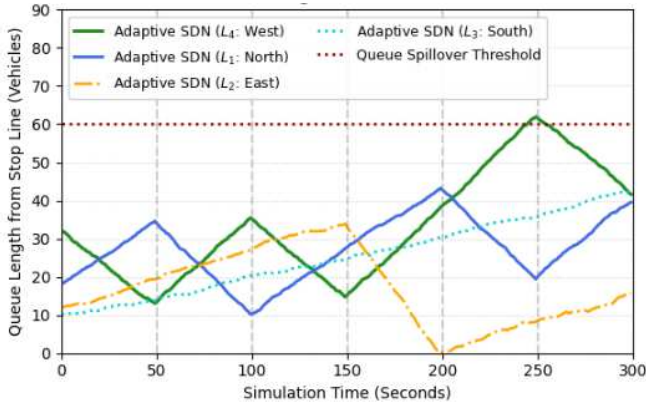


Fig.2 Queue Length Analysis

B. Lane-wise Queue Comparison

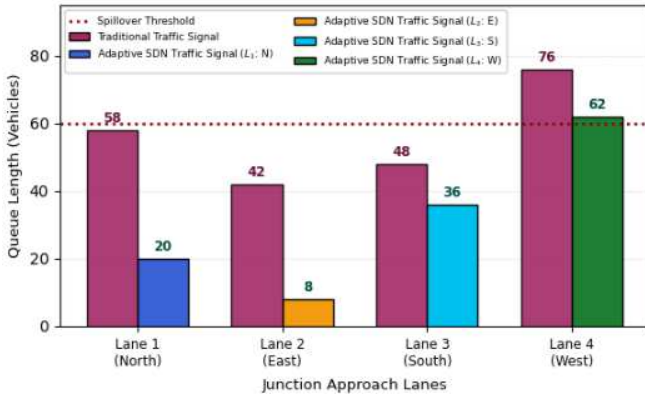


Fig.3 Lane-wise Queue Length at $t=250$ s

Fig. 3 compares the lane-wise queue lengths at $t=250$ s for the traditional traffic signal and the proposed Adaptive SDN Traffic Signal Control algorithm. The proposed approach significantly reduces congestion across all four lanes by dynamically prioritizing traffic demand. Queue lengths decrease from 58 to 20 vehicles in Lane 1, 42 to 8 vehicles in Lane 2, and 48 to 36 vehicles in Lane 3. Although Lane 4 experiences the highest traffic demand, the queue length is reduced from 76 to 62 vehicles, demonstrating the

ability of the proposed algorithm to mitigate congestion even under heavy traffic conditions.

C. Cumulative Vehicle Discharge Count

The proposed algorithm consistently achieves a higher vehicle discharge rate by dynamically prioritizing high-demand lanes. Over the 300-s simulation, it discharges 415 vehicles compared to 261 under traditional fixed-time control—a 59% throughput improvement (Fig. 4). This increase demonstrates that the Adaptive SDN Traffic Control algorithm mitigates green-time waste on empty lanes and maximizes saturation flow, significantly enhancing intersection efficiency by reducing queue accumulation.

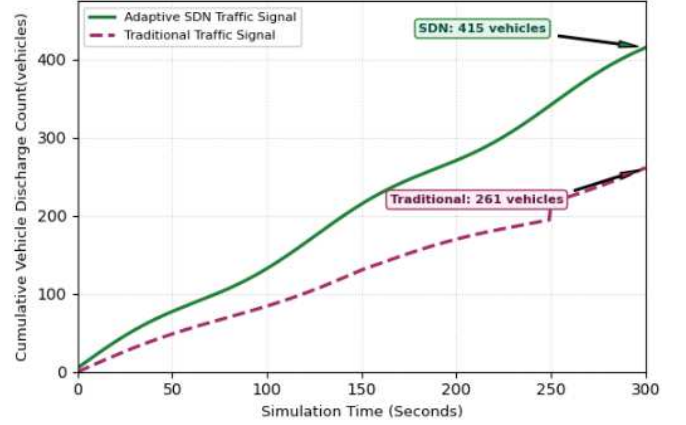


Fig. 4. Cumulative vehicle discharge count over time

D. Average Vehicle Waiting Time

As traffic volume scales from 100 to 250 vehicles, the traditional traffic signal experiences a sharp, non-linear increase in waiting time, exceeding 300 seconds at peak load due to fixed phase allocations, as depicted in Fig. 5. In contrast, the proposed Adaptive SDN algorithm maintains significantly lower delay across the entire evaluation range, starting at roughly 22 seconds and holding average waiting times to approximately 51 seconds under maximum load. Although EDTLCM [12] achieves lower baseline delay, the proposed approach drastically outperforms static signaling, proving that dynamic SDN scheduling effectively prevents severe queue buildup and minimizes latency under heavy congestion.

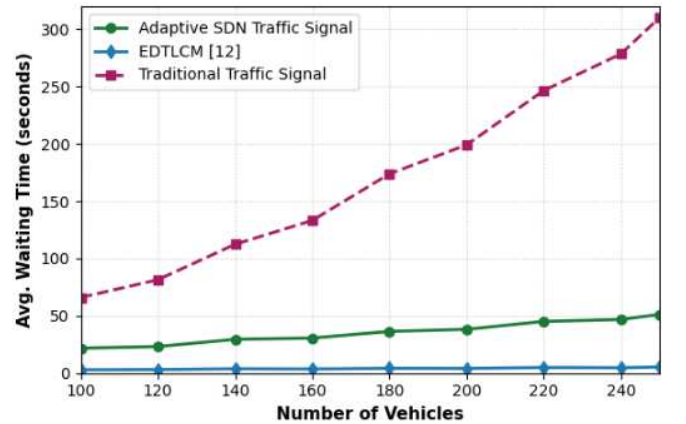


Fig. 5. Avg. vehicle waiting time vs. Number of vehicles

E. Average Fuel Consumption

As the traffic volume increases from 0 to 250 vehicles, fuel consumption rises across all schemes due to increased

congestion and vehicle queuing as shown in Fig. 6. The traditional traffic signal exhibits the highest fuel consumption, exceeding 8 mL/ vehicle at peak traffic load due to prolonged idling and frequent stop-and-go operations. In comparison, the proposed Adaptive SDN approach limits fuel consumption to approximately 5.6 ml per vehicle under the same conditions, indicating improved fuel efficiency over the conventional method. Although EDTLCM [12] achieves the lowest fuel consumption across all traffic scenarios, the proposed approach consistently reduces fuel usage relative to the traditional traffic signal, demonstrating the effectiveness of adaptive SDN-based traffic control.

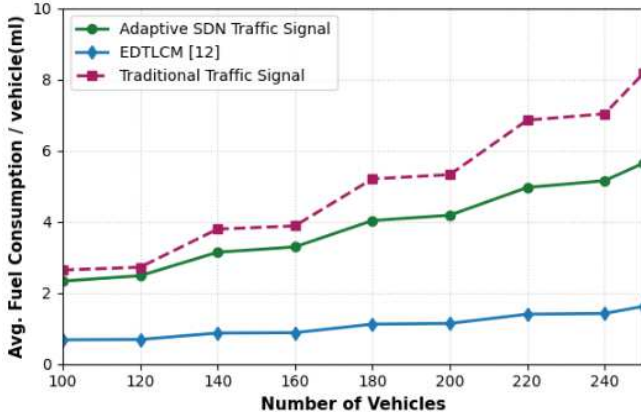


Fig. 6. Avg. Fuel Consumption per vehicle vs. Number of vehicles

F. Packet Delivery Ratio

Fig. 7 illustrates the Packet Delivery Ratio (PDR) of the proposed Adaptive SDN Traffic Signal, BCOOL-PAMPA 10MSG [13], and the traditional traffic signal as vehicle density scales from 50 to 150 vehicles. As traffic density increases, the PDR decreases for all schemes due to increased network congestion. The proposed Adaptive SDN approach maintains the highest PDR by clearing vehicle queues more efficiently, thereby reducing packet contention and transmission delays. In contrast, the traditional traffic signal experiences a significant decline in PDR because longer queues increase communication collisions and packet losses. These results demonstrate the effectiveness of adaptive SDN-based traffic control in maintaining reliable packet delivery under heavy traffic conditions.

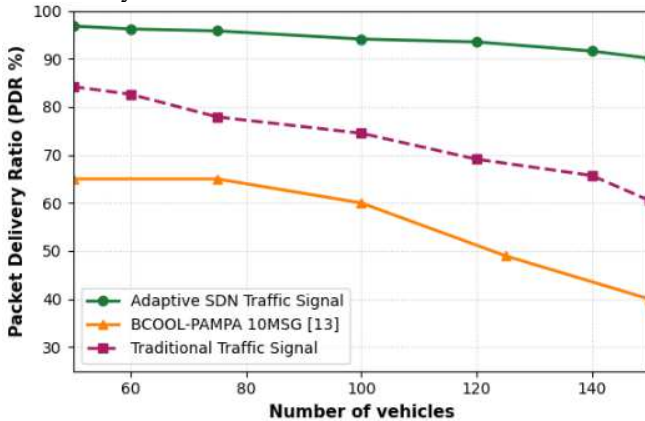


Fig. 7. PDR vs. Number of vehicles

G. Throughput

The proposed Adaptive SDN Traffic Signal consistently delivers higher throughput as traffic density increases, reaching approximately 1010 kbps at 150 vehicles as shown

in Fig. 8. In contrast, the traditional traffic signal and BCOOL-PAMPA 10MSG [13] exhibit throughput saturation at higher traffic densities due to increased congestion. The improved throughput is attributed to efficient queue clearance, which reduces packet contention and enables reliable data transmission.

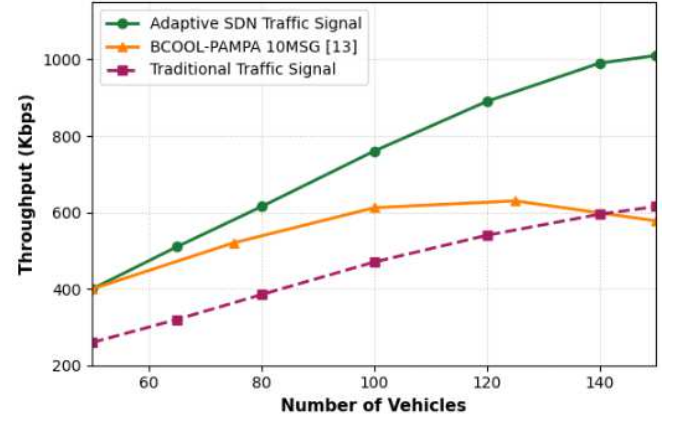


Fig.8. Throughput vs. Number of vehicles

H. Average E2E delay

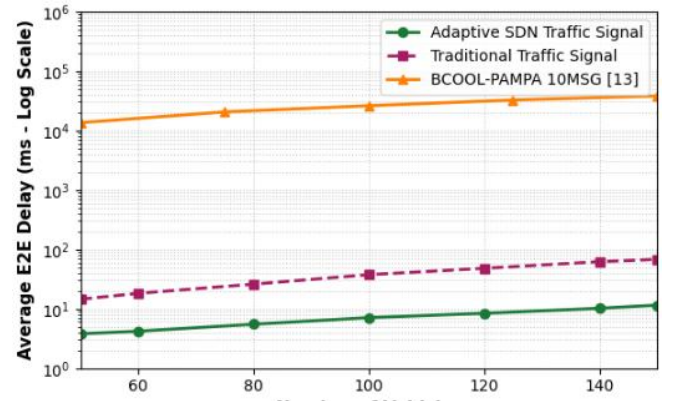


Fig.9. Avg.E2E delay vs. Number of vehicles

Fig. 9 illustrates the average end-to-end (E2E) delay under varying traffic volumes. The proposed Adaptive SDN Traffic Signal consistently maintains the lowest delay, increasing gradually from approximately 3.8 ms to 11.5 ms over the 50 to 150 range. In contrast, the traditional traffic signal exhibits a significant increase in delay due to congestion and prolonged queue formation, while BCOOL-PAMPA 10MSG [13] records the highest delay. The reduced delay of the proposed approach is achieved through efficient queue clearance, which minimizes packet contention and enables faster packet forwarding.

CONCLUSION

The experimental results demonstrate that the proposed Adaptive SDN-based traffic signal control scheme significantly improves overall traffic flow and communication performance compared to traditional signaling methods. By dynamically prioritizing and switching the green signal toward the lane with the longest queue, the proposed approach effectively mitigates average waiting time, fuel consumption, and end-to-end delay while sustaining a high packet delivery ratio and superior network throughput under scaling traffic density. These improvements stem from dynamic queue management, which prevents

physical vehicle accumulation, minimizes wireless channel contention, and enhances V2X communication reliability. Although specific baseline schemes achieve marginal gains in individual metrics, the proposed framework delivers a balanced, scalable solution that simultaneously optimizes physical mobility and network efficiency. Consequently, the Adaptive SDN Traffic Signal serves as a robust foundation for intelligent urban traffic management in high-density vehicular environments.

DECLARATIONS

- A. *Funding:*
This research received no external funding.
- B. *Clinical Trial Number:*
Not applicable.
- C. *Ethics, Consent to Participate, and Consent to Publish declarations:*
Not applicable.
- D. *Data Availability Statement:*
The dataset used in this study is a simulated dataset generated during the simulation experiments described in this manuscript. The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

REFERENCES

- [1] J. Li, L. Peng, K. Hou, Y. Tian, Y. Ma, S. Xu, and T. Z. Qiu, "Adaptive signal control and coordination for urban traffic control in a connected vehicle environment: A review," *Digital Transportation and Safety*, vol. 2, no. 2, pp. 89–111, 2023.
- [2] Z. Mo, W. Li, Y. Fu, K. Ruan, and X. Di, "CVLight: Decentralized learning for adaptive traffic signal control with connected vehicles," *Transportation Research Part C: Emerging Technologies*, vol. 141, Art. no. 103728, 2022.
- [3] C. Tan and K. Yang, "Privacy-preserving adaptive traffic signal control in a connected vehicle environment," *Transportation Research Part C: Emerging Technologies*, vol. 158, Art. no. 104453, 2024.
- [4] S. J. Rajan, S. Narayanaswamy, T. Balashanmugam, K. Sengottaiyan, A. Selvaraj, P. Majumder, A. Al-Rasheed, M. Getahun, and B. O. Soufiene, "Efficient traffic management with adaptive SDN in vehicular networks," *Scientific Reports*, vol. 15, Art. no. 11785, 2025.
- [5] S. M. Khan and M. Chowdhury, "Connected Vehicle Supported Adaptive Traffic Control for Near-congested Condition in a Mixed Traffic Stream," 2019.
- [6] H. Wei, G. Zheng, V. V. Gayah, and Z. Li, "A Survey on Traffic Signal Control Methods," *arXiv preprint arXiv:1904.08117*, 202.
- [7] G. Han et al., "Software-Defined Vehicular Networks: Architecture, Algorithms, and Applications: Part 1," in *IEEE Communications Magazine*, vol. 55, no. 7, pp. 78–79, July 2017, doi: 10.1109/MCOM.2017.7981529.
- [8] K. Abboud, H. A. Omar and W. Zhuang, "Interworking of DSRC and Cellular Network Technologies for V2X Communications: A Survey," in *IEEE Transactions on Vehicular Technology*, vol. 65, no. 12, pp. 9457–9470, Dec. 2016, doi: 10.1109/TVT.2016.2591558.
- [9] M. Gerla, E. -K. Lee, G. Pau and U. Lee, "Internet of vehicles: From intelligent grid to autonomous cars and vehicular clouds," 2014 IEEE World Forum on Internet of Things (WF-IoT), Seoul, Korea (South), 2014, pp. 241–246, doi: 10.1109/WF-IoT.2014.6803166.
- [10] Nick McKeown et al., "OpenFlow: Enabling Innovation in Campus Networks", *ACM SIGCOMM Computer Communication Review*, vol. 38, No. 2, Pages 69 – 74, 2008.
- [11] O. S. Al-Heety et al., "A Comprehensive Survey: Benefits, Services, Recent Works, Challenges, Security, and Use Cases for SDN-VANET", *IEEE Access*, vol. 8, pp. 91028–91047, 2020.
- [12] Hossan, S., Nower, N. Fog-based dynamic traffic light control system for improving public transport. *Public Transp* 12, 431–454 (2020). <https://doi.org/10.1007/s12469-020-00235-z>
- [13] S. Maaroufi and S. Pierre, "BCOOL: A Novel Blockchain Congestion Control Architecture Using Dynamic Service Function Chaining and Machine Learning for Next Generation Vehicular Networks," *IEEE Access*, vol. 9, pp. 53096–53122, 2021, doi: 10.1109/ACCESS.2021.3070023.
- [14] T. Balta, B. Ozcelik, and H. T. Kahraman, "A 3-stage fuzzy-decision tree model for traffic signal optimization in urban city via an SDN-based VANET architecture", *Future Generation Computer Systems*, vol. 104, pp. 142–158, 2020.
- [15] J. Peng, H. Huang, and L. Chen, "An adaptive traffic signal control in a connected vehicle environment: A systematic review," *information*, vol. 8, no. 3, Art. no. 101, 2017.
- [16] Y. Shi, Z. Wang, T. J. LaClair, C. R. Wang, Y. Shao, and J. Yuan, "A novel deep reinforcement learning approach to traffic signal control with connected vehicles," *Applied Sciences*, vol. 13, no. 4, Art. no. 2750, 2023.
- [17] J. Yang, J. Zhang, and H. Wang, "Urban traffic control in software defined Internet of Things via a multi-agent deep reinforcement learning approach," *IEEE Transactions on Network Science and Engineering*, vol. 8, no. 3, pp. 2221–2232, 2021.
- [18] M. A. Elhoseny et al., "SDN-assisted technique for traffic control and information execution in vehicular ad hoc networks," *Computers & Electrical Engineering*, vol. 102, Art. no. 108108, 2022.
- [19] T. Mekki, I. Jabri, A. Rachedi, and L. Chaari, "Software-defined networking in vehicular networks: A survey," *Transactions on Emerging Telecommunications Technologies*, vol. 33, no. 10, e4265, 2022.
- [20] S. Maadi, S. Stein, J. Hong, and R. Murray-Smith, "Real-Time Adaptive Traffic Signal Control in a Connected and Automated Vehicle Environment: Optimisation of Signal Planning with Reinforcement Learning under Vehicle Speed Guidance," *Sensors*, vol. 22, no. 19, Art. no. 7501, 2022.
- [21] M. Gillani, H. A. Niaz, M. U. Farooq, et al., "Data Collection Protocols for VANETs: A Survey," *Complex & Intelligent Systems*, vol. 8, pp. 2593–2622, 2022.