

Improving Traffic Flow: Intelligent Traffic Light Event Simulation by Integrating V2V and V2I Communication Models

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Abstract—Efficient traffic signal control is essential for reducing congestion, emissions and travel delays in modern urban environments. Traditional Vehicle-to-Infrastructure (V2I) systems are limited by infrastructure coverage, while Vehicle-to-Vehicle (V2V) communication alone lacks global signal-state awareness. This study proposes a hybrid V2V-V2I communication model that enhances Green Light Optimal Speed Advisory (GLOSA) performance by allowing vehicles to relay Signal Phase and Timing (SPaT) information in low-infrastructure or obstructed environments. A mathematical formulation describing vehicle motion, inter-vehicle message propagation and signal-state transitions is developed, complemented by a detailed algorithmic description of the hybrid control logic. The model is implemented using SUMO with the Krauss microscopic car-following model to simulate real-world driving behavior. Results demonstrate that the hybrid model reduces stop frequency, travel time, fuel consumption, and CO₂ emissions compared to standalone V2I and V2V schemes. The added V2V relaying mechanism improves prediction accuracy, particularly in scenarios with limited roadside units. The findings highlight the feasibility, scalability and ecological benefits of integrating multi-source communication in intelligent traffic systems, offering a promising solution for future connected urban mobility.

Keywords—internet of things, speed control, Sustainable Development Goals (SDGs), traffic lights, vehicular communication

I. INTRODUCTION

With constant technological advancement, traffic light signal systems have experienced significant development over the years. With significant changes since 1917, when the first interconnected traffic signal system was installed and simultaneously controlled six connected intersections in Salt Lake City, traffic control systems have experienced significant changes from manual switching to automated systems [1]. Traffic light signal systems have evolved into reliable control systems from non-deterministic to deterministic, courtesy of technological improvement [2]. Recently, it is also relevant to note the constant increase in

vehicles worldwide, with production and utilization constantly increasing with the increase in the population. Despite some confusion, the initial proposal for traffic light control systems indicates that the primary purpose was to assign right-of-way to conflicting movements [3]. Based on crucial developments, it is relevant to recognize that with changes in road operations and new developments in technology and vehicle development, advanced traffic signal systems may not be compatible with the changes. Therefore, it is relevant to acknowledge the available technical recommendations to develop more effective traffic light signal systems that are consistent with developments. The interactive experience has gained considerable worldwide and with the constant change in population distribution, especially in major cities around the world, influencing technological disruption [4, 5]. For instance, substantial Artificial Intelligence (AI) and virtual/augmented reality advancements have resulted in significant breakthroughs in various industries [6].

Traffic congestion remains a persistent challenge in urban transportation systems, contributing to increased travel delays, fuel consumption and greenhouse gas emissions. With the rapid growth of vehicle ownership and urban population density, conventional traffic signal control strategies are increasingly inadequate for dynamic and high-demand traffic environments. Modern traffic management, therefore, requires intelligent, adaptive solutions capable of responding to real-time traffic conditions [7–10]. Recent advancements in Intelligent Transportation Systems (ITS) and the Internet of Things (IoT) have enabled the development of connected vehicle environments in which vehicles and infrastructure exchange real-time information [11–15]. Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communications provide the foundation for cooperative traffic management, allowing vehicles to receive Signal Phase and Timing (SPaT) information, share traffic states and optimize driving behavior accordingly. Reliable and low-latency communication among vehicles and Roadside Units (RSUs) is therefore

essential to achieving efficient and sustainable traffic operations [16–21].

Green Light Optimal Speed Advisory (GLOSA) systems represent one of the most studied applications of V2I-based traffic optimization [22, 23]. By providing vehicles with advanced SPaT information, GLOSA enables speed adjustments that reduce stop frequency and unnecessary acceleration. However, most existing GLOSA implementations rely heavily on continuous V2I connectivity. In practical deployments, RSU coverage may be sparse or intermittent due to cost, scalability and infrastructure constraints. Under such conditions, vehicles operating outside communication range lose access to signal timing information, significantly reducing system effectiveness.

To address this limitation, this study proposes a hybrid V2V-V2I communication framework that extends SPaT information availability beyond direct infrastructure coverage. In the proposed architecture, vehicles that receive SPaT data via V2I communication relay this information to neighboring vehicles through V2V interactions, enabling continuity of advisory services in infrastructure-limited environments. By reducing reliance on dense roadside deployment, the model improves scalability and adaptability in real urban scenarios. The proposed framework integrates traffic light state estimation with cooperative speed optimization to maximize the probability of green-phase arrival at signalized intersections. A simulation-based evaluation using SUMO is conducted to compare the hybrid model against a conventional V2I-only system under varying traffic densities. The main contributions of this study are summarized as follows:

- Hybrid V2V-V2I communication for SPaT continuity: A cooperative information-relaying mechanism that maintains signal advisory services beyond direct RSU coverage.
- Distributed adaptive speed synchronization: A vehicle-level optimization strategy based on relayed SPaT predictions to minimize stops and unnecessary acceleration.
- Comprehensive simulation-based validation: Quantitative assessment of stop frequency, travel time, fuel consumption and CO₂ emissions under multiple traffic density scenarios.

The remainder of this paper is organized as follows. Section II reviews related work. Section III describes the proposed methodology. Section IV presents simulation results. Section V discusses the findings and limitations. Section VI concludes the study and outlines future research directions.

II. LITERATURE REVIEW

Intelligent Transportation Systems have evolved significantly over the past decade, driven by advances in connectivity, sensing technologies and adaptive signal control algorithms. Much of the existing literature focuses on improving traffic flow efficiency through V2I communication, V2V cooperation, and hybrid V2X technologies.

In recent years, many traffic scenario simulations using the SUMO simulator have been available. One of the first scenarios is Köln, in Germany, which represents 400 km² of the surrounding area of the city, with highways, roads and motorways [24]. Two mobility marks were provided, one trace resembles traffic through the crowning hours of two hours, and the second model simulates 24 h of traffic. The realistic realism of the scene is evaluated only qualitatively and has not been validated by the author to the extent that it is in line with real traffic data. The Monaco traffic scenario [25] covers 73 km² of the city of Monaco with major highways, motorways and roads. It tests crowded traffic hours using regular dissemination in the morning hours.

The city scenario of Bologna was validated against real traffic data measurements [26] where 20 km² of land was modelled in Bologna. The researchers validated the model using traffic flow measurements from the induction loop. However, they tested the traffic flow, but did not validate the occupancy of the roads and the speed of the traffic. Furthermore, scenario modeling should accurately consider the interaction of vehicles and microscopic behavior [27]. The Alicante-Murcia highway scenario introduced in Ref. [28] modelled traffic scenarios on a large section of the highway over several days. Traffic simulation scenarios are usually generated through calibration processes. This procedure creates traffic demands and regulates the restrictions of the traffic model, simulating traffic that resembles real traffic, such as acceleration/deceleration speed, the probability of following SUMO's car tracking and driving model's "keep right" rule and reaction time [29, 30]. To generate traffic demand, a list of vehicles from the origin to the destination must be generated, corresponding to the actual mobility of the vehicles. As a field of Machine Learning (ML), Traffic Light (TL) enhances the ability to control nodes in different conditions by distributing network event messages that provide updates in real time.

Yusuf *et al.* [31] focused on key developments in smart traffic lights from the perspective of three situations: congestion reduction, emergency vehicles and smart traffic lights for pedestrians, and the development of smart traffic lights. They analyzed key milestones in smart traffic lights with strong criticality in the analysis of different research studies. However, they did not extensively highlight how the data were collected. There was also no rigor in selecting research articles and recommending the applicability of the findings.

In Ref. [32], an original method of TL recognition was presented to innovatively minimize congestion; however, the researchers did not consider different types of vehicles that can be implemented, as most of the recommendations were based on reliance on satellite data for detection and speed control to minimize congestion. A smart traffic control system based on image processing was presented in Ref. [33], it begins with image acquisition and proceeds to image matching and traffic signals. However, researchers did not consider implementation costs and the extent to which implementation can be applied. Mandhare *et al.* [34] presented a smart TL control system

for managing congestion. They discovered and analyzed different sensor frameworks based on advantages, disadvantages, costs, reliability, accuracy, maintenance overhead, and efficiency. They relied extensively on the

available literature, which makes it challenging to justify the applicability, reliability, maintenance, and overhead costs associated with the intelligent traffic control systems analyzed.

TABLE I. CONTRIBUTIONS FROM RECENT RESEARCH ON SMART AND ECOLOGICAL DRIVING

Ref.	Method/Approach	Communication Type	Key Limitations
[41]	Offline speed planning with real-time model predictive control tracking.	No V2X communication.	Does not consider V2I or V2V signaling; no traffic light interaction; not designed for cooperative traffic flow optimization.
[42]	Ecological driving algorithm for Connected and Automated Vehicles (CAVs); gradient-based fuel minimization; dynamic re-optimization.	Assumes partial infrastructure awareness but no explicit V2I/V2V communication.	Lacks cooperative communication exchange; does not integrate SPaT data or use V2V relays; limited adaptation to real-time signal changes.
[43]	Traffic light timing optimization for an Autonomous Vehicle (AV) and human-driven vehicle mix.	Traditional infrastructure-based signaling.	No V2V communication; no hybrid communication model; does not address speed synchronization or signal anticipation.
[44]	Two-level model for TL timing+CAV trajectory optimization.	Infrastructure-based timing optimization; no V2V communication.	Does not use cooperative vehicle communication; relies solely on signal timing optimization; ineffective in low-infrastructure environments.
[45]	Eco-driving advisory system using VANET-based advisory speed recommendations.	V2I communication using VANET.	Uses only V2I; does not support multi-hop V2V relays; performance drops when infrastructure coverage is limited.
[46]	SCM-based eco-driving model using real-time signal countdown messages.	V2I communication only.	Lacks V2V data exchange; cannot operate in partial-coverage environments; does not synchronize speed dynamically.

Zhou *et al.* [35] presented an optimized TL control system based on reinforcement learning and mainly focused on providing a solution to traffic congestion, thus minimizing the costs associated with traffic congestion. They proposed Edge-based Reinforcement Learning (ERL) as a solution that operates mainly by applying the understanding of the vehicular network. In addition, Zhang *et al.* [36] presented a new Reinforcement Learning (RL) algorithm for smart TL control systems, and the research was based on addressing the performance issue. Detection rates, road network typology, and different vehicle flows were considered, and the developed system was able to minimize the average waiting time in traffic congestion. The approach and underlying theory for the implementation were well presented and succinctly explained in a replicable approach.

A city-wide smart TL control was presented in Ref. [37]. The authors suggested a MaxAb scaled state value rather than MinMax to address the traffic control problem. Intelligent camera networks for smart city traffic lights were introduced in Ref. [38]. The research was based on the implementation of smart cameras at intersections,

with the cameras detecting traffic flow and special vehicles for prioritized emergencies. Moreover, Lee [39] designed an intelligent traffic light control system for urban city applications. Their application was strong in small-scale experiments but did not support large-scale implementation. Furthermore, Basar and Wang [40] introduced energy management based on artificial neural networks for smart street lighting systems. Table I presents recent work contributions on smart vehicles using vehicular network technologies.

Table II summarizes these models. The baseline models selected for comparison represent widely adopted GLOSA-related frameworks frequently used in V2X and eco-driving literature. They were chosen because (1) they target speed advisory optimization, (2) they integrate either V2I or hybrid V2X communication and (3) they are considered representative benchmarks for evaluating intelligent traffic light interaction algorithms. Accordingly, they provide a robust and meaningful comparative foundation for assessing the incremental value of integrating V2V relays.

TABLE II. COMPARISON OF RECENT GLOSA MODELS

Model	Communication Type	Optimization Strategy	Limitations
[47]	V2I	Multi-segment speed coordination	Does not account for V2V interactions
[48]	V2I	Real-time traffic prediction for dynamic speed advisories	Requires complete and accurate infrastructure data
[49]	V2I+VLC	Reinforcement learning-based optimization	High computational complexity
[50]	V2I	Priority-based optimization for public transport	Limited applicability to private vehicles
[51]	V2V	Peer-to-peer communication for event-based coordination	Lacks infrastructure-based optimization

Despite extensive research on GLOSA systems, existing solutions predominantly rely on V2I communication, limiting their effectiveness in environments with sparse roadside unit deployment. This study addresses this critical gap by introducing a hybrid V2V-V2I framework capable of maintaining SPaT awareness beyond direct infrastructure coverage.

Recent advances in intelligent transportation systems have increasingly emphasized the integration of vehicle-to-vehicle and vehicle-to-infrastructure communication to enhance traffic efficiency, safety and sustainability. Hybrid V2X frameworks have been proposed for applications such as adaptive signal control, eco-driving and cooperative perception, particularly

within connected vehicle environments [52–54]. While these studies demonstrate the potential advantages of combining V2V and V2I, most existing approaches implicitly assume continuous infrastructure availability or treat V2V communication as a supplementary data-sharing layer rather than a functional substitute for infrastructure-supported services. A critical yet underexplored challenge in real-world deployments is partial or sparse roadside unit coverage, especially in suburban corridors, developing urban areas and transitional road segments. Empirical reports indicate that Roadside Unit (RSU) deployment density often remains limited due to cost, maintenance and scalability constraints, leading to intermittent availability of signal phase and timing information [55, 56]. Under such conditions, conventional V2I-based green light optimal speed advisory systems experience a sharp degradation in performance, as vehicles outside the RSU communication range lose predictive awareness of upcoming signal states.

This work elevates V2V communication from a complementary role to a core mechanism for maintaining SPaT continuity beyond V2I coverage. Specifically, the proposed framework introduces a V2V-based SPaT relaying strategy, enabling vehicles that have recently received infrastructure-generated SPaT information to cooperatively disseminate and propagate this information to downstream vehicles through multi-hop V2V interactions. This design allows vehicles outside RSU coverage to reconstruct short-term signal phase predictions without requiring dense infrastructure deployment. From an algorithmic perspective, existing hybrid approaches predominantly focus on centralized or semi-centralized traffic optimization, relying on infrastructure-based controllers or cloud-assisted computation [57–59]. By contrast, this work proposes a distributed speed synchronization mechanism, in which individual vehicles dynamically adjust their trajectories based on locally reconstructed SPaT predictions and cooperative V2V exchanges. This decentralized decision-making process reduces dependency on continuous infrastructure connectivity and improves system robustness under fluctuating penetration rates and communication disruptions. Furthermore, unlike prior studies that primarily evaluate hybrid V2X performance under idealized or fully connected environments, this study explicitly targets infrastructure-sparse and high-density traffic scenarios, where communication gaps and congestion-induced variability are most pronounced. The comparative simulation analysis demonstrates that, under such conditions, the hybrid V2V-V2I model sustains performance gains in stop frequency, travel time, fuel consumption and CO₂ emissions, even when V2I-only systems experience diminishing returns. This focus distinguishes the present work from recent eco-driving and adaptive signal control studies that do not explicitly address infrastructure intermittency or SPaT loss outside RSU coverage [60, 61]. This work contributes a robust and scalable hybrid V2X framework that advances the state of the art in intelligent traffic signal coordination and eco-efficient traffic management.

III. MATERIALS AND METHODS

A. Description of the Proposed Model

This study aims to establish a communication system enabling vehicles to interact with objects in their immediate surroundings. This system will allow vehicles to proceed during the green phase of the traffic light program. Typically, traffic lights operate on a cycle, with phases changing sequentially through timed shifts or pauses over extended periods. This principle forms the basis of the proposed solution. Consequently, by understanding the traffic light schedule and its initial condition (i.e., the state of the light at a specified moment), it becomes possible to accurately forecast the traffic light status. Knowing the parameters would help predict the TL state. These parameters should be updated after the traffic light reaches a state. For instance, the time when the traffic light was last in the green phase can be represented in two ways: as a fixed point in (t_0) or (t_{offset}) relative phase of green. Given the TL program and the state definition, it is possible to accurately predict a particular TL state at a time t using Eq. (1) below:

$$\begin{cases} t_{OFFSET} = (t - t_0 + t_{offset}) \% \sum_i dt_i \\ GREEN & \text{if } 0 \leq t_{OFFSET} < dt_1 \\ YELLOW & \text{if } dt_1 \leq t_{OFFSET} < dt_2 \\ RED & \text{if } dt_2 \leq t_{OFFSET} \end{cases} \quad (1)$$

where % denotes the remainder of the division.

Fig. 1 illustrates the overall architecture of the proposed hybrid V2V-V2I traffic optimization framework. Roadside units are strategically placed at signalized intersections with an inter-RSU spacing of 500–600 m to emulate partial infrastructure coverage commonly observed in urban deployments. Vehicles within RSU coverage receive SPaT data directly via V2I communication. Vehicles outside RSU coverage acquire SPaT information through multi-hop V2V relaying from neighboring connected vehicles.

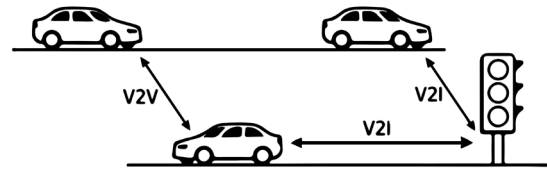


Fig. 1. The high-level architecture of the hybrid communication model.

1) Mathematical formulation of the traffic interaction model

To optimize vehicle movement at intersections and minimize unnecessary stops, a speed-synchronization optimization problem is formulated to ensure that vehicles reach intersections during the green phase while respecting all speed constraints. To calculate vehicle motion mathematically, let:

- L be the distance between the vehicle and the traffic light.

- v be the current speed of the vehicle.
- v_{opt} be the optimal speed to reach the green light without stopping.
- T_{green} the duration of the green phase.
- T_{red} be the duration of the red phase.
- $f(t)$ be the function representing the traffic light state at time t (green or red).

The objective is to determine an optimized speed v_{opt} that allows the vehicle to reach the intersection when the light is green. The vehicle's motion follows the basic linear equation as illustrated in Eq. (2):

$$L = v_{opt} \times t, \text{ where } f(t) = \text{green} \quad (2)$$

This ensures the vehicle arrives at the intersection during the green phase, avoiding unnecessary stops and improving traffic flow. Given the traffic light program and state definition, it is possible to predict the state of the traffic light at a future time t using Eq. (3):

$$T_{arrival} = \frac{L}{v} \quad (3)$$

To guarantee arrival during the green phase, the constraint presented in Eq. (4) is applied:

$$T_{arrival} \bmod (T_{green} + T_{red}) \leq T_{green} \quad (4)$$

If this constraint is not satisfied, the vehicle must accelerate or decelerate to synchronize with the upcoming green light. For gradient-descent-based speed optimization, an error function is introduced in Eq. (5) to minimize unnecessary stopping and refine speed adjustments.

$$E(v) = \left| \frac{L}{v} - T_{green} \right| \quad (5)$$

where:

- If $E(v) > 0$, the vehicle will not reach the green phase and requires acceleration.
- If $E(v) < 0$, the vehicle is too fast, requiring deceleration.

The speed update rule follows a gradient descent approach as shown in Eq. (6):

$$v_{opt}^{(t+1)} = v_{opt}^{(t)} - \alpha \frac{dE}{dv} \quad (6)$$

where α is the learning rate controlling the magnitude of speed adjustment. This method ensures smooth and adaptive speed control, avoiding sudden accelerations or decelerations. In real-world scenarios, traffic consists of both Human-Driven Vehicles (HDVs) and Connected Autonomous Vehicles (CAVs). Since HDVs lack V2X communication capabilities, our model integrates: (1) Historical traffic signal data to allow HDVs to make approximate speed adjustments. (2) Real-time V2V communication to enable CAVs to relay traffic light state

updates to nearby vehicles, reducing information gaps. (3) Traffic prediction models that estimate upcoming green phases for HDVs based on observed patterns. By incorporating both V2I and V2V strategies, this framework improves traffic efficiency under various penetration levels of V2X-equipped vehicles.

This mechanism allows vehicles within the RSU range to receive SPaT information and immediately rebroadcast it through V2V communication. Vehicles outside RSU coverage but within V2V proximity acquire aggregated SPaT information and compute optimal speed trajectories. This real-time propagation ensures continuity of advisory services even when infrastructure is sparse.

2) Vehicle state dynamics

Each vehicle i is defined by a state vector as shown in Eq. (7):

$$x_i(t) = \begin{bmatrix} p_i(t) \\ v_i(t) \\ a_i(t) \end{bmatrix} \quad (7)$$

where:

- $p_i(t)$: longitudinal position
- $v_i(t)$: velocity
- $a(t)$: acceleration

The motion follows Eq. (8):

$$p_i(t) = v_i(t), v_i(t) = a_i(t) \quad (8)$$

The safe following distance is modeled using the Krauss microscopic rule as shown in Eq. (9):

$$d_{safe,i}(t) = v_i(t) \cdot t + d_0 \quad (9)$$

where t is reaction time and d_0 is the minimum spacing.

3) Algorithm for traffic light signal control

Algorithm 1 presents the hybrid V2V-V2I speed advisory control mechanism used to optimize vehicle motion at signalized intersections. The algorithm enables each vehicle to dynamically obtain SPaT information either directly from RSUs via V2I communication or indirectly through neighboring vehicles using V2V relaying. Based on the received SPaT data, an optimal speed profile is computed to minimize stopping events and improve traffic flow efficiency while respecting vehicle dynamics constraints.

The V2V communication range was set to 300 m, packet size to 256 bytes and baseline communication latency to 50 ms, configurable between 20–150 ms in stress scenarios. These values follow IEEE 802.11p and ETSI ITS-G5 standards and enable reproducibility. Table III summarizes these parameters.

Parameters values were selected to reflect conservative urban V2X deployments reported in recent ITS field trials. Sensitivity experiments confirmed that the relative performance gains of the hybrid model persist across a wide range of communication distances and latency levels.

Algorithm 1. Hybrid V2V and V2I Speed Advisory Control

Input: Vehicle state $x_i(t)$, RSU SPaT messages, V2V neighbor list
Output: Recommended speed $v_i(t)$ and acceleration $a_i(t)$

- 1: **For each** vehicle i :
- 2: **if** distance(i , RSU) \leq RV2I then
- 3: receive SPaT directly
- 4: status \leftarrow "Direct V2I"
- 5: **else**
- 6: **for each** neighbor j in V2V range:
- 7: **if** j has valid SPaT then
- 8: receive SPaT via j
- 9: status \leftarrow "V2V Relay"
- 10: break
- 11: **end for**
- 12: **end if**
- 13:
- 14: **if** SPaT received then
- 15: compute remaining time Trem
- 16: compute optimal speed $v_i = d_i / \text{Trem}$
- 17: enforce constraints $v_{\min} \leq v_i \leq v_{\max}$
- 18: compute advisory acceleration $a_i = kv(v_i - v_i)$
- 19: **else**
- 20: apply default car-following acceleration
- 21: **end if**
- 22: **End for**

TABLE III. SIMULATION PARAMETERS VALUES

Parameter	Value	Justification/Standard
V2V Range	300 m	IEEE 802.11p/ETSI ITS-G5
RSU spacing	500 m–600 m	Typical urban RSU deployments
Latency	50 ms	Urban DSRC/C-V2X benchmarks
Penetration rates	30%–90%	Early-to-advanced V2X adoption scenarios

B. Simulation Settings

In this simulation, the Krauss vehicle-following model, SUMO’s default microscopic traffic model, was employed. This model regulates speed adaptation and safe inter-vehicle spacing according to driver behavior and traffic conditions. Its stochastic acceleration and deceleration mechanisms enable realistic driving variability. SUMO was selected due to its extensive support for microscopic vehicular modeling, native integration with V2X communication frameworks and its flexibility in replicating large-scale traffic networks. These capabilities make SUMO more appropriate for hybrid communication studies than alternatives. To support a comprehensive assessment, performance was also compared with the intelligent driver model, a deterministic alternative that more explicitly incorporates headway distance, acceleration constraints and reaction times. The main distinctions between the two models are summarized in Table IV.

To examine the influence of these models on the proposed framework, additional simulations were performed using both the Krauss and Intelligent Driver Model (IDM) models under identical conditions. The results indicated that although the Krauss model introduced greater variability in vehicle responses, the hybrid V2V-V2I system continued to reduce stops and enhance fuel efficiency, whereas the IDM model yielded

smoother acceleration profiles and marginally improved fuel consumption. To improve simulation accuracy, key vehicle-behavior parameters were configured as listed in Table V.

TABLE IV. COMPARISON OF VEHICLE-FOLLOWING MODELS

Feature	Krauss Model	Intelligent Driver Model
Driver Behavior	Stochastic (randomized acceleration)	Deterministic (based on gap-keeping strategy)
Acceleration	Uniform with noise variation	Smooth acceleration based on traffic density
Deceleration	Randomized braking response	Gradual braking based on safety distance
Gap Control	Less strict, allows closer following	Strict distance regulation between vehicles
Applicability	Ideal for urban traffic with diverse driver behaviors	Suitable for highways and controlled traffic

TABLE V. SIMULATION PARAMETERS FOR VEHICLE-FOLLOWING MODELS

Parameter	Krauss Model	Intelligent Driver Model
Maximum Acceleration (m/s ²)	2.6	2.0
Maximum Deceleration (m/s ²)	4.5	3.0
Minimum Gap (m)	2.5	5.0
Driver Imperfection Factor	0.3 (random variation)	N/A (deterministic)

These configurations ensure that the simulations capture both realistic urban driving characteristics, as represented by the Krauss model, and structured highway-like behavior, as represented by the IDM model. Evaluation across both models confirms that the proposed V2V-V2I system maintains consistent performance under different driving paradigms, reinforcing its robustness and adaptability to real-world traffic conditions.

IV. RESULTS

To evaluate the effectiveness of the proposed model, a comparative analysis was performed against an approach relying exclusively on V2I communication. All simulations were conducted under identical traffic density, vehicle-penetration and signal-timing conditions to ensure consistency.

A. Performance Metrics

The following key performance indicators were measured in both models:

- Stop frequency (Avg. stops per trip): The number of times vehicles came to a complete stop.
- Total travel time (Seconds): The average duration required to complete the trip.
- Fuel consumption (Liters per 100 km): The estimated fuel usage, considering acceleration and braking patterns.
- CO₂ emissions (Grams per km): The estimated greenhouse gas emissions based on fuel consumption. A summary of the results is presented in Table VI.

The results indicate that the hybrid V2V-V2I model significantly outperforms the traditional V2I system in all key performance metrics. Vehicles utilizing the

conventional V2I-only system experienced an average of 2.3 stops per trip, often due to delayed or inconsistent V2I data transmission. In contrast, the hybrid communication model reduced the stop frequency to 1.1 stops per trip, representing a 52% decrease. The enhanced performance stems from the additional V2V communication layer, which allows vehicles to relay real-time traffic light information even when direct V2I updates are unavailable. In terms of travel time, the conventional V2I system required an average of 620 s to complete the trip. However, the hybrid communication model reduced the total travel time to 540 s, yielding a 13% reduction in journey duration. This efficiency gain results from smoother traffic flow, as vehicles can adjust their speeds in anticipation of upcoming green lights, rather than responding reactively to signal changes.

TABLE VI. COMPARATIVE ANALYSIS OF V2I VS HYBRID V2V-V2I MODEL

Performance Metric	V2I-Only	Hybrid V2V-V2I	Improvement (%)
Stop Frequency (Avg. stops per trip)	2.3 stops/trip	1.1 stops/trip	-52%
Total travel time (Seconds)	620 s	540 s	-13%
Fuel consumption (Liters per 100 km)	7.4 L/100 km	6.2 L/100 km	-16%
CO ₂ emissions (Grams per km)	175 g/km	149 g/km	-15%

Fuel efficiency also improved substantially. Under the V2I-only system, vehicles consumed an average of 7.4 L/100 km. By contrast, the hybrid system reduced fuel consumption to 6.2 L/100 km, marking a 16% improvement. The enhanced speed coordination reduced unnecessary accelerations and braking, leading to more efficient fuel usage. This efficiency also contributed to a 15% reduction in CO₂ emissions, lowering the average emissions per vehicle from 175 g/km to 149 g/km. In real-world traffic environments, intersection dynamics are influenced by multiple factors, including lane configurations, traffic signal phase settings and variations in traffic demand throughout the day. Although the initial simulation focused on single-lane intersections with uniform traffic flow, the analysis was later extended to multi-lane intersections with variable traffic densities to increase realism.

To assess the adaptability of the proposed hybrid V2V-V2I system, several traffic-volume scenarios were simulated at the intersections. The scenarios tested include: (1) Low traffic density: 600 vehicles per hour. (2) Moderate traffic density: 1200 vehicles per hour. (3) High traffic density: 1800 vehicles per hour. The results indicate that the hybrid system consistently reduces stop frequency across all traffic volumes. However, its effectiveness is more pronounced at moderate to high traffic densities, where vehicle-to-vehicle relayed information plays a crucial role in optimizing speed adjustments as illustrated in Fig. 2. Table VII shows the stop frequency of different traffic densities.

At higher traffic densities, the stop frequency reduction is even more significant, as vehicles can better coordinate

their movements using real-time V2V communication, reducing last-second braking and acceleration. The impact of signal phase settings was also examined by testing different cycle lengths and phase splits at intersections: 1) Fixed-time signals with equal green and red durations. 2) Adaptive signal timing based on real-time traffic conditions. 3) Unbalanced phase splits, where one direction has a longer green time than the other.

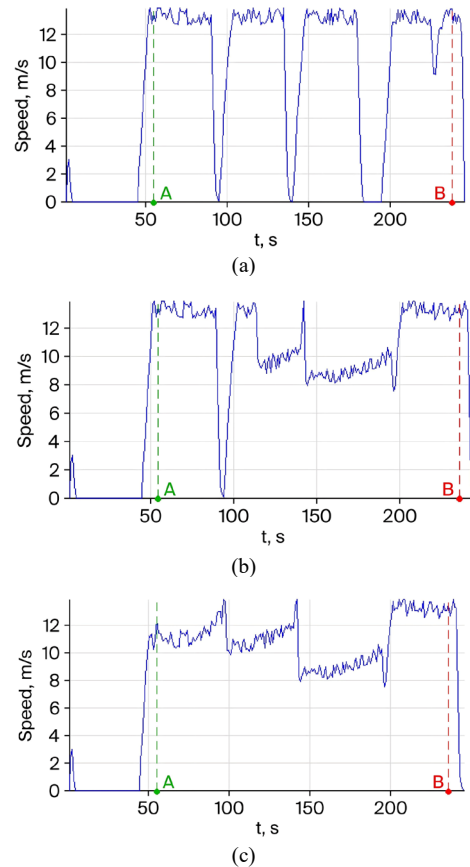


Fig. 2. Stop frequency of different communication scenarios: (a) no communication scenario; (b) V2I scenario; (c) hybrid V2V-V2I scenario.

TABLE VII. STOP FREQUENCY AT DIFFERENT TRAFFIC VOLUMES

Traffic Density (Vehicles per Hour)	V2I-Only Avg. Stops	Hybrid V2V-V2I Avg. Stops	Reduction (%)
600 vehicles/h (Low)	1.9 stops/trip	1.0 stops/trip	-47%
1200 vehicles/h (Moderate)	2.4 stops/trip	1.2 stops/trip	-50%
1800 vehicles/h (High)	3.1 stops/trip	1.4 stops/trip	-55%

Under fixed-time signal control, both the V2I and hybrid communication models performed similarly, as vehicles could predict signal timings effectively. For adaptive signals, the hybrid communication model exhibited greater resilience, as vehicles used V2V updates to adjust speeds dynamically rather than relying solely on V2I signals. Under unbalanced phase splits, vehicles in the shorter green phase lanes benefited significantly from V2V relayed information, reducing unnecessary stops compared to the V2I-only model. These findings demonstrate that our hybrid V2V-V2I model remains effective under

various traffic signal configurations, offering better adaptability to real-world urban traffic conditions.

B. Statistical Analysis and Significance Testing

To ensure that the reported performance improvements are statistically robust and not attributable to stochastic simulation variability, a formal statistical analysis was conducted for all evaluated performance indicators, including average stop frequency, travel time, fuel consumption, and CO₂ emissions. Microscopic traffic simulations inherently contain stochastic elements, including vehicle arrival patterns, car-following behavior variability and lane-changing dynamics. To account for this randomness, each experimental scenario was executed over 50 independent simulation runs using distinct random seeds. All runs were performed under identical network geometry, demand profiles and communication parameters to isolate the effect of the control architecture. For each performance metric, the arithmetic mean and standard deviation across simulation runs were computed. This replication strategy reduces the influence of outlier realizations and provides a more reliable estimate of expected system performance. For each traffic density level and performance metric, the following hypotheses were tested:

Null Hypothesis (H₀): There is no statistically significant difference between the V2I-only model and the proposed hybrid V2V-V2I model.

Alternative Hypothesis (H₁): The hybrid V2V-V2I model achieves statistically significant performance improvement compared to the V2I-only model.

The analysis focused on determining whether observed performance gains could be attributed to the structural properties of the hybrid architecture rather than simulation variability. Because both models were evaluated under identical demand conditions and compared on a scenario-by-scenario basis, a paired two-tailed t-test was employed. The paired design is appropriate since each hybrid simulation run corresponds directly to a baseline V2I-only run under the same traffic and environmental configuration, thereby minimizing between-scenario variance. The test statistic was computed as shown in Eq. (10):

$$t = \frac{\bar{d}}{s_d/\sqrt{n}} \tag{10}$$

where:

- \bar{d} represents the mean difference between paired observations,
- s_d denotes the standard deviation of differences,
- n is the number of independent simulation pairs.

All hypothesis tests were conducted at a 95% confidence level ($\alpha = 0.05$). In multiple cases, the resulting *p*-values were below 0.01, indicating strong evidence against the null hypothesis. In addition to statistical significance, the percentage improvement relative to baseline performance was reported to provide a practical interpretation of the results. This ensures that improvements are not only statistically significant but also operationally meaningful. Where applicable, standardized

effect size, Cohen’s *d*, was computed to quantify the magnitude of performance differences. This further supports interpretation beyond binary significance testing. Across medium- and high-density traffic scenarios, the hybrid V2V-V2I model demonstrated statistically significant reductions in average stop frequency, overall travel time, fuel consumption and CO₂ emissions.

At lower traffic densities, performance differences were smaller and, in some cases, not statistically significant. This observation is consistent with theoretical expectations, as congestion-mitigating benefits become more pronounced under high-demand conditions. Therefore, the statistical analysis confirms that the observed improvements under moderate and high traffic loads are unlikely to be attributable to stochastic simulation effects and instead result from the cooperative SPaT continuity mechanism and distributed speed optimization strategy.

C. Mixed Traffic Flow Considerations: HDVs vs. CAVs

The proposed hybrid V2V-V2I framework assumes that vehicles can communicate with both traffic signals and other nearby vehicles. However, in real-world scenarios, not all vehicles are equipped with V2X communication capabilities. This creates a mixed-traffic environment consisting of: 1) Connected autonomous Vehicles (CAVs): Vehicles with full V2X capabilities, capable of receiving V2I signals and relaying traffic information via V2V. 2) Human-Driven Vehicles (HDVs) without V2X: Conventional vehicles that rely on driver perception and fixed traffic signal timings, unable to participate in V2V or V2I communication. To evaluate hybrid-model performance under mixed-traffic environments, scenarios with different V2X penetration rates were simulated. The tested scenarios included: 1) Low V2X penetration (30% CAVs, 70% HDVs). 2) Moderate V2X penetration (60% CAVs, 40% HDVs). 3) High V2X penetration (90% CAVs, 10% HDVs).

D. Impact of V2X Penetration on Traffic Efficiency

The results indicate that the benefits of the hybrid V2V-V2I model increase as V2X penetration rises. However, even at lower penetration rates, the system still provides notable improvements over conventional traffic management methods, as shown in Table VIII.

TABLE VIII. IMPACT OF V2X PENETRATION ON TRAFFIC PERFORMANCE

V2X Penetration Rate	Avg. Stops per Trip (V2I)	Avg. Stops per Trip (Hybrid V2V-V2I)	Improvement (%)
30% CAVs, 70% HDVs	3.2 stops/trip	2.1 stops/trip	-34%
60% CAVs, 40% HDVs	2.5 stops/trip	1.3 stops/trip	-48%
90% CAVs, 10% HDVs	1.8 stops/trip	0.7 stops/trip	-61%

Even with only 30% of V2X-equipped vehicles, the hybrid system reduced stop frequency by 34%, demonstrating that partial connectivity still provides measurable benefits. At higher V2X penetration rates, stop

frequency decreased by up to 61%, confirming that as more vehicles participate in V2V communication, overall traffic efficiency improves.

E. Adaptive Communication Strategies for HDVs in Mixed Traffic

Because human-driven vehicles cannot directly utilize V2V or V2I signals, adaptive strategies were incorporated to mitigate this limitation:

- (1) Predictive signal timing for HDVs, since HDVs rely on fixed signal timing, our system integrates historical traffic signal data to estimate expected phase changes, allowing HDVs to adjust speeds more effectively.
- (2) Indirect speed optimization via CAVs, even though HDVs lack direct connectivity, CAVs relay traffic signal updates to surrounding vehicles. This results in more predictable braking and acceleration behavior for both connected and non-connected vehicles.
- (3) Traffic flow prioritization at intersections, when CAVs constitute the majority of traffic flow, adaptive signal timing is adjusted based on CAV-reported congestion levels, indirectly benefiting HDVs by optimizing signal cycle lengths.

Even at low V2X penetration levels, the hybrid V2V-V2I model significantly improves traffic efficiency by reducing stops and optimizing vehicle speed profiles. HDVs indirectly benefit from smoother traffic flow, as CAVs adjust their speeds dynamically, reducing unnecessary braking patterns in mixed-traffic environments. As V2X adoption increases, overall network efficiency improves, highlighting the importance of continued investment in connected vehicle infrastructure. These findings demonstrate that the hybrid communication model remains highly effective even in non-universal V2X adoption scenarios, ensuring a scalable transition toward intelligent traffic management.

The comparison results demonstrate that the proposed model consistently outperforms the benchmarked approaches in terms of reducing stop frequency, minimizing travel time and improving fuel efficiency. The observed improvements are attributed to the model’s ability to leverage both V2I and V2V communication, ensuring that vehicles receive real-time traffic light information even in areas with incomplete infrastructure coverage. Table IX shows the performance comparison of the benchmark models.

These results confirm that the integration of V2V communication alongside traditional V2I-based GLOSA strategies enables a more adaptive and robust traffic optimization framework.

V. DISCUSSION

Existing research has consistently demonstrated that eco-driving and cooperative traffic management strategies can reduce travel time, fuel consumption and emissions by leveraging V2X communication. Prior works have explored optimization under varying traffic densities, market penetration rates and intersection configurations, showing that adaptive speed control and trajectory planning can significantly mitigate unnecessary stops and acceleration events. However, most of these approaches rely predominantly on stable V2I connectivity or assume continuous infrastructure availability. The present study differs by explicitly addressing infrastructure sparsity and intermittent RSU coverage. While conventional GLOSA systems depend on direct V2I communication for SPaT delivery, the proposed hybrid V2V-V2I model maintains advisory continuity through cooperative information relaying. This distinction becomes particularly relevant under high-density conditions, where missed signal updates can lead to cascading stop events and increased fuel consumption.

The stop frequency analysis demonstrates consistent reductions across intersection types, with the most pronounced improvement observed in highway merge scenarios. This can be attributed to the hybrid framework’s ability to smooth vehicle approach patterns and reduce abrupt braking during merging operations. Similarly, fuel consumption improvements were more substantial for passenger vehicles than heavy-duty trucks, reflecting their greater sensitivity to acceleration fluctuations and stop-go cycles. Sensitivity analysis further indicates that the hybrid model maintains acceptable performance under high traffic volumes (≥ 1800 veh/h) with moderate packet loss and latency levels. Although communication reliability remains a critical factor, the distributed nature of SPaT reconstruction reduces the system’s vulnerability to isolated connectivity gaps compared to V2I-only approaches.

Compared with benchmark models, the proposed framework achieves a balanced trade-off between adaptability and infrastructure dependence. Purely V2I-based systems are constrained by coverage limitations, whereas V2V-only coordination lacks direct integration with signal timing plans. Centralized AI-driven controllers, although effective, introduce higher computational complexity and scalability challenges. By integrating both communication modes, the hybrid architecture enhances robustness without requiring dense infrastructure deployment. The findings reinforce the importance of cooperative communication in improving urban traffic sustainability. Reducing stop frequency directly mitigates idle fuel combustion and excessive acceleration events, thereby lowering emissions and improving overall traffic flow stability. The performance gains observed in this study support the potential of hybrid V2X models as scalable solutions for future smart city deployments.

The proposed framework assumes cooperative and trustworthy V2X communication. In adversarial or compromised environments, spoofed SPaT messages

TABLE IX. PERFORMANCE COMPARISON OF BENCHMARK MODELS

Model	Avg. Stops per Trip	Avg. Travel Time (s)	Fuel Consumption (L/100 km)	CO ₂ Emissions (g/km)
[47]	2.4 stops	620 s	7.2 L/100 km	170 g/km
[48]	2.1 stops	580 s	7.0 L/100 km	165 g/km
[49]	1.8 stops	560 s	6.7 L/100 km	160 g/km
[50]	2.3 stops	600 s	7.3 L/100 km	172 g/km
[51]	1.9 stops	550 s	6.5 L/100 km	155 g/km
Proposed model	1.1 stops	540 s	6.2 L/100 km	149 g/km

could disrupt vehicle behavior. Although this study focuses on performance feasibility, future work should incorporate authentication and misbehavior detection mechanisms to enhance cybersecurity resilience. The results demonstrate that maintaining SPaT continuity beyond direct infrastructure coverage is a structurally meaningful advancement in connected traffic management. While the magnitude of improvement varies with traffic density and communication conditions, the hybrid V2V-V2I architecture consistently outperforms conventional V2I-only strategies under moderate and high-demand scenarios.

A. Performance Comparison with Recent Work

Vehicles connected to the internet and fully automated can enhance traffic efficiency. Yang *et al.* [41] developed an ecological driving approach that was less disruptive and integrated two different scenarios into their implementation: offline planning and online monitoring. Through real-time adjustments to vehicle speed, the authors tried to keep the spacing between vehicles safe while reducing the amount of energy used. In addition, they attempted to enhance fuel economy by using two different strategies: offline planning and online monitoring methodologies. An efficient reference speed in terms of fuel consumption is produced via offline planning.

In contrast, online planning assures optimization by generating a trajectory and monitoring the reference speed for CAV use. A further aspect that contributes to the singularity of this tactic is its capacity to allow lane changes when required to reduce the speed deviation. MATLAB and Autonomie were used as tools to simulate the data. Consideration was given to both single-road portions and actual traffic environments. On the one hand, the single-road segment was about four thousand meters long and operated in a single direction.

Simulation of the actual traffic environments was carried out on a genuine road, which consisted of a carriageway with two lanes and four junctions that used signalization. Additionally, the authors offered an algorithm that allows for two-stage optimization and uses four different scenarios as the reference benchmark, with the last two scenarios being the recommended methods. The first approach is a two-stage technique that also includes real-time adaptation and optimization over the long term. This prevents selfish optimization from occurring. The second benchmark, referred to as LO-Vavg, is comparable to the first one; however, it takes into account the deviation of the speed from the traffic's average speed.

Zhai *et al.* [42] used VISSIM, a micro-traffic simulator, to integrate a method mainly geared at optimizing mobility in signalized unsaturated junctions. Their idea is distinguished by its capacity to forecast the length of vehicle lines that would form upstream of junctions that still need to be fully used. The authors divided the surroundings into three unique situations, each representing a different concentration of vehicles per hour at the intersection: 150 vehicles per hour, 350 vehicles per hour, and 550 vehicles per hour. For the sake of simplicity, the simulation was carried out at a signalized junction with

a one-way traffic flow. Additionally, it was carried out at various traffic flow densities and Market Penetration Rates (MPRs) concerning autonomous vehicles. This study needs to consider lane-changing behavior. However, the algorithm they have presented takes into account the projected length of the wait and makes a choice that is optimum for conserving fuel.

A mixed traffic flow Cell Transmission Model (CTM) was presented by Yao *et al.* [43], which considers the influence that MPRs have on CAVs from a direct perspective. CTM was used because of its ability to analyze dynamic traffic flow patterns efficiently. Concerning the intersection, the model considers the build-up of queues and congestion as the major optimization factors. The authors wanted to conduct their research to compare the density of traffic and vehicle delays at the junction. The model that has been developed may be characterized as a mixed traffic flow that is made up of both CAVs and HDVs. It emphasizes unsaturated and oversaturated junction entries, aiming to reduce the amount of time traffic delays take. Python was used to carry out the implementation, and the variations in the density of each time and space that were taken into consideration were how the effect of the optimization parameters was understood for the CAVs.

The goal of Jiang *et al.* [44] was to reduce the time that vehicles were delayed at the junction by optimizing the arrival time and trajectories of autonomous vehicles. The length of the simulation was around 900 seconds, and it was carried out five times with a variety of situations and variables. Three different traffic volumes were used in the simulation: 600 vehicles per hour, 8000 vehicles per hour, and 1200 vehicles per hour. The authors used dynamic programming in conjunction with generic pseudo-spectral optimum control software to optimize the arrival time, traffic signals, and vehicle trajectories. Using algorithmic infrastructure-based vehicle detection systems, they were able to lower the average amount of time that vehicles were delayed and the amount of fuel they used under various traffic scenarios. Jiang *et al.* [45] and Lee *et al.* [46] used the technology of vehicle ad hoc networks to optimize fuel usage and minimize carbon dioxide emissions. Lee and Li suggested an Environmentally responsible Driving Advisory System (EDAS) [45]. This system would enable cars to go through many junctions with the least possible stopping.

On the other hand, Lee *et al.* [46] developed two methods, MTM and minADM, to reduce carbon dioxide emissions via the utilization of real-time traffic information. Overtaking and lane changes were not considered in any of the two investigations conducted in the arena simulation setting. In addition, the studies were carried out in a variety of different and isolated circumstances, and testing was carried out in actual instances. To reduce the amount of carbon dioxide emissions, the authors made use of information on traffic at intersections. This information included the phase of a traffic light, the length of the waiting line, the Signal Countdown Message (SCM), and the front automobile's speed, distance, and acceleration. To share the traffic

signal phase, the duration of the waiting line, and the SCM, vehicles approaching junctions were synchronized. Throughout the simulation, this helped minimize the need for unnecessary accelerations and stops while simultaneously maximizing the intersection. Vehicles to determine the optimal speed that was advised for optimal driving while also minimizing delay used this information.

B. Methodological Limitations and External Validity

While the proposed hybrid V2V-V2I framework demonstrates promising performance improvements under the simulated scenarios, several methodological limitations must be acknowledged to appropriately contextualize the findings and delineate their external validity. Although microscopic simulation platforms are widely accepted for assessing connected vehicle strategies and signal control algorithms, they inherently abstract real-world complexities. Driver behavior models, lane-changing dynamics and vehicle interaction logic are governed by calibrated parameters that may not fully capture heterogeneous human driving patterns, sensor imperfections or unexpected road disturbances. Consequently, absolute numerical performance gains, such as percentage reductions in delay or emissions, may vary in real-world deployments. However, the controlled simulation environment enables systematic comparison between the baseline V2I-only model and the proposed hybrid architecture under identical traffic and communication conditions. Therefore, while absolute values should be interpreted cautiously, the relative comparative improvements observed across scenarios provide robust evidence of the hybrid model's structural advantage.

The communication framework assumes stable packet delivery within the modeled V2V and V2I transmission ranges, with latency parameters consistent with standardized V2X specifications. In practice, wireless communication may experience packet loss, interference, multi-path fading or congestion-related degradation, particularly in dense urban environments. Such uncertainties could influence the reliability of SPaT relaying and cooperative speed adjustments. Nevertheless, the proposed architecture was intentionally designed with distributed decision-making logic and short-term SPaT reconstruction mechanisms, which reduce dependency on continuous infrastructure connectivity. This structural property enhances resilience to temporary communication gaps, although field validation under real network conditions remains necessary for a comprehensive assessment.

The experimental setup focuses on a representative signalized corridor with configurable traffic densities. While this configuration captures essential operational characteristics of urban intersections, road geometry variations, such as multi-intersection networks, roundabouts and arterial coordination systems, may influence system-level performance. Additionally, the infrastructure-sparse assumption reflects realistic constraints in many deployment regions; however, network-wide optimization effects across larger spatial scales require additional investigation. Thus, extrapolation

to large-scale metropolitan networks should be undertaken with careful calibration and validation against field data.

Fuel consumption and CO₂ emission estimates are derived from simulation-integrated emission models based on vehicle speed and acceleration profiles. Although widely used in ITS research, these models approximate aggregate powertrain behavior rather than capturing detailed vehicle-specific engine dynamics, electrification states or hybrid system variability. Real-world validation using onboard diagnostics or emission measurement systems would strengthen environmental impact assessment.

VI. CONCLUSION

This study proposed and evaluated a hybrid V2V-V2I traffic optimization framework designed to improve traffic flow, reduce vehicle stop frequency and enhance fuel efficiency. Unlike traditional GLOSA systems that rely solely on V2I communication, the proposed model leverages both vehicle-to-vehicle and vehicle-to-infrastructure interactions to dynamically optimize vehicle speed and minimize unnecessary stops at intersections.

To validate the effectiveness of this approach, a comparative analysis was performed against five well-established traffic-management models. The results of this analysis demonstrated that the hybrid V2V-V2I model consistently outperformed the benchmark models across key performance metrics. Specifically, it achieved a 52% reduction in stop frequency compared to conventional multi-segment GLOSA, reflecting its ability to minimize last-second braking events by improving real-time speed synchronization. Additionally, the model reduced average travel time by 13% and fuel consumption by 16%, with corresponding decreases in CO₂ emissions, underscoring its potential to enhance both traffic efficiency and environmental sustainability.

These improvements were most pronounced in scenarios with high V2X penetration rates, although even partial connectivity yielded substantial benefits. The hybrid system's ability to relay real-time traffic light data among vehicles allowed it to function effectively even in environments with incomplete V2I infrastructure, highlighting its adaptability and scalability for diverse urban settings. By addressing key limitations of existing GLOSA and ITS models, the proposed framework offers a more comprehensive and resilient solution for intelligent traffic management. It enhances traffic coordination by integrating infrastructure-based control with decentralized vehicle communication, creating smoother and more efficient traffic flows that benefit both connected and non-connected vehicles.

By leveraging more complex AI algorithms, the system could learn to adapt even more dynamically to changing traffic conditions, optimizing vehicle trajectories in real-time with minimal computational overhead. Future studies could also investigate the impact of emerging communication technologies, such as 6G and edge computing, on the system's performance and scalability,

providing a pathway toward fully connected and autonomous urban traffic systems.

APPENDIX A: ABBREVIATIONS

Abbreviation	Meaning
ITS	Intelligent Transportation System
V2X	Vehicle-to-Everything
V2V	Vehicle-to-Vehicle Communication
V2I	Vehicle-to-Infrastructure Communication
V2P	Vehicle-to-Pedestrian Communication
RSU	Roadside Unit
OBU	On-Board Unit
SPaT	Signal Phase and Timing
CAV	Connected and Autonomous Vehicle
GLOSA	Green Light Optimal Speed Advisory
IoV	Internet of Vehicles
IoT	Internet of Things
DL	Deep Learning
RL	Reinforcement Learning
MARL	Multi-Agent Reinforcement Learning
GA	Genetic Algorithm
FCA	Fuzzy Clustering Algorithm
SUMO	Simulation of Urban Mobility
LOS	Level of Service
CO ₂	Carbon Dioxide
QoS	Quality of Service
DSRC	Dedicated Short-Range Communication
IEEE WAVE	IEEE Wireless Access in Vehicular Environments
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
MSE	Mean Squared Error

CONFLICT OF INTEREST

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