

Scalable and interoperable C-V2X framework for real-time intelligent decision support in autonomous mobility

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ABSTRACT: While V2X-based vehicle communication and intersection management have been widely studied, most existing approaches remain limited to simulation-based environments or constrained testbeds. Furthermore, standardized message formats such as SAE J2735 lack the extensibility required to support emerging autonomous vehicle services, leading to inefficient or inflexible system implementations. To address these limitations, this study proposes a modular, edge-intelligent framework—the mobility operating system (mOS)—integrated with a mixed-reality testbed for realistic validation of infrastructure-guided autonomous vehicle coordination. The proposed mOS supports plug-and-play integration of V2X communication modules, real-time intersection management algorithms, and bidirectional interactions between physical and virtual agents. Scenarios involving vehicle-to-vehicle and vehicle-to-pedestrian interactions were conducted to evaluate the effectiveness of mOS under realistic latency and behavioral uncertainty. Key performance metrics, including vehicle speed trajectory and communication latency, were used to measure the responsiveness and accuracy of coordination. The results confirm that the mOS successfully improves safety and behavioral predictability under complex intersection scenarios. This study demonstrates the feasibility of Mixed reality integrated infrastructure intelligence and offers a scalable pathway for deploying AV coordination systems in next-generation innovative mobility ecosystems.

KEYWORDS: scalable cooperative-intelligence transportation system (C-ITS) framework; customized message set; intelligent intersection guidance; mixed reality environment; testbed demonstration

1 Introduction

The cooperative-intelligence transportation system (C-ITS) is emerging as a crucial technology for autonomous driving and smart city development. The underlying infrastructure required for its implementation is steadily evolving (Chester and Allenby, 2019). To support the development of autonomous driving and smart cities, cellular vehicle-to-everything (C-V2X) has emerged as a foundational pillar within C-ITS. C-V2X has evolved to connect vehicles, infrastructure, pedestrians, and networks through a high-reliability, low-latency communication structure based on LTE/5G (Sehla et al., 2022). In particular, collision prevention (Fu et al., 2022; Wu et al., 2020) and route decision support (Alabdouli et al., 2025) at complex intersections require the real-time sharing of information between vehicles and infrastructure.

Several efforts have been made to resolve these problems. However, they have several limitations that hinder their ability to handle the task in a scalable and interoperable manner. First, most existing C-V2X applications are center-focused methods, where traffic information is collected, processed, and broadcast to nearby vehicles. These systems rely on post event analysis without performing localized runtime intelligent processing or decision-making for vehicles. As a result, vehicles independently interpret the given information and make their own driving decisions for cooperative maneuvers (Hubmann et al., 2017). Although this approach can be effective in simple situations and is often sufficient to ensure individual vehicle safety, it becomes inefficient in complex environments, such as unsignalized intersections or mixed-traffic roads, for various reasons, such as the unknown intentions of users (Liu et al., 2019; Wang et al., 2019), motion planning under uncertainty (Xu et al., 2014) and an occluded

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environment (Yang et al., 2019). To address these limitations, there is a growing need for infrastructure-level intelligence that can interpret the traffic context and support intersection-level coordination to improve overall traffic flow.

Second, the standardized binary message set structure used in C-V2X communication, such as SAE J2735 and ETSI ITS-G5, has proven effective for specific applications, including signal phase and timing (SPaT) processing at signalized intersections. However, as traffic environments become increasingly diverse and dynamic, this rigid structure presents significant limitations. Modifications to the traditional message set structure often cause compatibility issues with existing devices, hindering interoperability and increasing both development complexity and the risk of errors (Agbaje et al., 2022). These constraints are particularly evident in scenarios requiring flexible and context-aware interactions, such as unsignalized intersections where vehicles must negotiate priority (Wang et al., 2021). In such cases, static speed and location data conveyed through predefined binary formats are insufficient to support cooperative maneuvering.

Third, even with improvements in network communication, physical-world road environments present additional challenges due to the diversity of road users. In the near future, road users will consider not only fully connected autonomous vehicles (CAVs) but also traditional traffic modes, such as human-driven vehicles, pedestrians, and micromobility. Many of these modes lack V2X communication functionality, making it fundamentally difficult to achieve complete situational awareness or ensure safe interaction on the basis solely of connected data.

To address these challenges, we propose the mobility operating system (mOS), a scalable and interoperable framework for real-time intelligent decision support for autonomous mobility. To address the first and second challenges mentioned above, we explore two complementary approaches. The adoption of flexible and extensible message formats, such as JSON and XML, enables richer semantic representation and facilitates the communication of complex situational contexts beyond the constraints of fixed schemas. Second, the integration of publish-subscribe-based communication protocols, such as MQTT, provides a scalable and dynamic messaging infrastructure that supports real-time, low-latency data exchange across heterogeneous systems. These approaches can enhance the utilization of V2X communication systems, particularly in environments demanding complex, context-aware interactions. Therefore, a message set architecture that emphasizes both flexibility in data representation and scalability in communication is necessary for disunified communication.

We leverage serverless containerization, a plug-and-play architecture, to overcome the third challenge. This architecture supports the dynamic integration of edge-computing-based components and functional modules, enabling each intersection to analyze traffic situations and make context-aware decisions autonomously. By encapsulating V2X communication modules, decision algorithms, and coordination logic into portable containers, the system can be rapidly deployed, updated, and scaled across heterogeneous infrastructure setups. This modularity allows infrastructure nodes to selectively activate context-specific functions, such as pedestrian detection and conflict zone negotiation, on the basis of local needs and available capabilities.

Furthermore, containerized modules can be orchestrated both locally and across multiple intersections, enabling cooperative behaviors without relying on a fully centralized cloud system. This approach enhances adaptability, promotes interoperability, and simplifies integration with future traffic systems. Embedding

intelligence in this modular way ultimately supports scalable and efficient management of autonomous and cooperative driving scenarios. To demonstrate the feasibility of the proposed architecture, physical world experiments are limited by safety and cost concerns at intersections with high-risk or irregular road environments. To safely and cost-effectively validate the proposed framework, this study designed a mixed reality (MR) experimental environment utilizing metaverse-based digital twin technology. The environment is configured to reflect real-time traffic infrastructure and vehicle status in the virtual space, simulating interactions with virtual objects, including vehicles and pedestrians. The proposed modular infrastructure system is tested and verified within this MR environment, allowing safe testing of the core algorithms, including object prediction behavior, priority judgment, and speed control. Metaverse technology offers a flexible experimental environment that enables repeated simulations of various driving scenarios, eliminating physical infrastructure and communication network constraints, and evaluating the effectiveness of driving strategies for each situation.

2 Literature review

In this section, we review the relevant literature concerning components that include C-V2X, intersection guidance, and MR environments, with a specific emphasis on initiatives aimed at harmonizing traditional systems. Following this, we conduct a critical analysis of the literature, identifying any gaps and assessing the study's contribution to the broader body of literature.

2.1 Network communication

Vehicular ad hoc networks (VANETs), built on ITS-G5 via the IEEE 802.11p standard, have long supported vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication (Committee, 2009). However, they face key limitations, such as a limited communication range (Maglogiannis et al., 2022), network congestion in dense traffic (Bansal et al., 2013), and a lack of nonline-of-sight (NLoS) coverage (Mertens et al., 2020). To address these issues, C-V2X, standardized by 3GPP in Release 14 and further enhanced in Release 16, offers an alternative with dual communication modes (direct and network-based), improved scalability in high-density scenarios, extended coverage, and enhanced security and interoperability (Abdel Hakeem et al., 2020).

As 5G technologies mature, C-V2X is positioned as a critical enabler for ITSs and autonomous driving, leveraging ultrareliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communication (mMTC) (Abdel Hakeem et al., 2020). Its design combines direct PC5 interface communication for time-sensitive, local exchanges with network-based modes for broader coverage and cost-effective integration with the cellular infrastructure. However, relying solely on centralized cloud computing introduces latency and scalability issues, rendering it inadequate for real-time, safety-critical applications such as collision avoidance.

To overcome these challenges, C-V2X is evolving into a cloud-edge continuum (Bréhon-Grataloup et al., 2022; Feng et al., 2023; Moubayed et al., 2021; Pereira et al., 2023). Distributed edge computing processes critical data locally at roadside units (RSUs) and onboard vehicle units (OBUs), ensuring ultralow latency for immediate safety responses such as collision avoidance at intersections (Bréhon-Grataloup et al., 2022; Feng et al., 2023; Pereira et al., 2023) and warning of occlusion (Narri et al., 2025). Moreover, the centralized cloud aggregates large-scale traffic patterns and infrastructure data for long-term planning and

optimization (Bréhon-Grataloup et al., 2022; Feng et al., 2023). The integration of 5G and multiaccess edge computing (MEC) further enhances this model by enabling URLLC, reducing dependence on centralized servers, and supporting real-time, data-driven decision-making, which is essential for safe and efficient ITS deployment. In this study, we adopt a hybrid edge-cloud C-V2X architecture to validate its practical applicability.

2.2 Message set

The message set defines the messages, data structures, and data elements required for V2X communication to support C-ITS and CAV services. Unlike the underlying network, physical, or MAC layer standards (e.g., WAVE or Cellular), the message set is largely communication-agnostic. Currently, the widely used message set is SAE J2735 (Sumner et al., 2013).

J2735 specifies standardized messages, such as the basic safety message (BSM), SPaT, map data (MAP), and traveler information message (TIM), which are structured in the ASN.1 format for efficient encoding and interoperability between devices, including RSUs and OBUs. Accordingly, messages are selectively utilized on the basis of the data requirements of the C-ITS and autonomous driving services. The BSM, for example, contains essential safety-related information about a vehicle, such as its position, speed, heading, and type, as well as additional vehicle status data. Owing to these characteristics, the BSM has been widely adopted as a core component in many C-ITS and autonomous driving applications (Ahmed-Zaid et al., 2011; Feng and Liu, 2019; Hu et al., 2025; Lee et al., 2021). Similarly, SPaT and MAP messages are used to support real-time traffic signal information services (Levin et al., 2023; Wagner et al., 2023), whereas the TIM facilitates data exchange for vehicle warning systems (Hatcher et al., 2024). However, if the data required by a specific service is not defined in the existing message set, the service must either use the external region field to specify new data or define an entirely new message to support implementation.

On the basis of a review of the widely adopted SAE J2735 standard message set, although J2735 offers advantages in terms of communication efficiency and interoperability between devices, it also presents several limitations when used for CAV services. The first issue stems from the origin of the J2735 standard, which was initially developed to support ITS services in DSRC environments. As a result, its data structures are not optimized for the advanced requirements of autonomous driving. Consequently, to implement CAV services, all messages containing the necessary data must be transmitted—even if only a portion of the data is needed—leading to communication inefficiencies. Second, as CAV services become more sophisticated, the range of data requirements is growing; however, the J2735 message set lacks flexibility and scalability to keep pace with these evolving needs. When new services are designed on the basis of existing J2735 messages, developers must extend the ASN.1 structure to define new data or add new message types together. This scalability challenge becomes particularly pronounced in autonomous driving environments where diverse and high-volume sensors and control data exchanges are essential.

2.3 Intersection control via guidance

CAVs have advanced significantly, using sensors and AI for accurate navigation. However, onboard sensors are limited in range and can be obstructed by buildings or other vehicles, making it difficult to rely solely on internal perception in complex traffic environments. To address these limitations, research has focused on integrating communication capabilities (Khayatian et

al., 2020) that expand the CAV perception range and enable negotiation with other vehicles and infrastructure (Strykowski et al., 2021). This connectivity enables new approaches to control intersections beyond traditional signals by instructing and controlling CAVs.

Traditional traffic signals allocate time-space resources by allowing vehicles in specific lanes to cross during designated intervals, preventing conflicts. In contrast, intelligent intersection management enabled by CAV connectivity allows more sophisticated control and is typically categorized into trajectory planning, reservation-based, and traffic signal-based methods. Trajectory planning uses optimization to generate precise, conflict-free paths; however, it faces physical world challenges because of its high computational demands (Malikopoulos and Zhao, 2019). While effective in simulations, these methods require complex scheduling to avoid collisions (Chen and Englund, 2016). Reservation-based systems allocate time-space slots through a request-accept mechanism, offering efficient, scalable, and low-cost coordination. Traffic signals remain essential for human-driven vehicles (HVs), with proposed adaptations such as dedicated CAV phases or hybrid signaling to ensure safe interaction with mixed traffic (Rey and Levin, 2019).

While research into autonomous intersection management (AIM) methods has yielded promising results in terms of safety and efficiency, their physical world applicability remains largely untested. While existing studies have demonstrated significant improvements in traffic efficiency, they have largely been confined to simulations (Chen and Englund, 2016). Some physical tests have been conducted, but these have been limited to scenarios involving a single real vehicle within a simulation loop (Quinlan et al., 2010) or have been carried out in isolated test environments that do not accurately reflect the complexities of the actual road infrastructure (Fayazi et al., 2019). The physical world is fundamentally different from that of simulations. Critical factors such as communication delays, vehicle dynamics, and environmental noise are often assumed to be ideal in theoretical studies. To further develop intersection management systems that are suitable for physical world applications, it is essential to conduct tests that closely replicate physical world conditions.

2.4 MR environments

MR is a complex concept, and research on MR is relatively limited compared with that on virtual reality (VR) and augmented reality (AR), as MR lies at the intersection of the VR and AR horizons. VR immerses users in an entirely virtual environment, separating them from the physical world. In contrast, AR overlays virtual elements in the physical environment, typically limiting one-way interaction with virtual objects. In previous research, investigations have been conducted on the interaction between virtual and physical objects that influence dynamic responses, such as those of rubber corn (Yeo et al., 2019), reindeer (Goedicke et al., 2022), and buildings (Ghiurau et al., 2020), within an onboard system. This research demonstrates the use of a mixed traffic environment for actual driving scenes using on-road driving with an actual vehicle. Similarly, research using generative AI creates virtual objects (Xu et al., 2023) and synthesizes them with real images, allowing for one-way interaction.

MR, however, enables dynamic interaction between physical and virtual objects, allowing both environments to influence each other. For example, Argui et al. (2024) utilized a small-scale testbed with toy cars to simulate interactions. In contrast, Drechsler et al. (2022) developed a framework that integrates actual and virtual vehicles within a test field and control center.

This study demonstrates the feasibility of MR but provides limited details on the specific implementation methods. Although previous research has made progress in MR-based CAV testing, many approaches remain limited in terms of interactivity and the bidirectional influence between virtual and actual entities.

2.5 V2X system architecture with messaging protocols

Conventional V2X network communication systems enable collaborative perception among vehicles by exchanging informative messages, including vehicle position, velocity, and acceleration. According to Liu et al. (2023), recent V2X systems rely on a cloud platform in conjunction with OBU/RSU communications, enabling vehicles and infrastructure to exchange perception information (Liu et al., 2023) and lane-changing intentions (Xu et al., 2019). However, these systems typically follow a centralized management paradigm, where all data are processed in the cloud or on a dedicated server. This structural design reveals communication latency and computational burden, posing inherent limitations for localized intersection management.

To address these limitations, researchers have introduced edge cloud architectures, which bring computational resources closer to end users at the network edge, thereby enhancing the service capabilities of 5G systems (Maller et al., 2022). Leveraging Kubernetes for efficient orchestration of containerized applications, edge cloud platforms have been explored for use cases, such as smart city air quality monitoring (Böhm and Wirtz, 2022) and handover across service zones via traffic simulation (Maller et al., 2022), and autoscaling systems that adapt to device request traffic (Phuc et al., 2022). Nevertheless, the application of Kubernetes-based edge cloud architectures to physical world intersection management remains rare.

Unlike the standard V2X messaging protocol, MQTT offers the advantage of transmitting diverse message types with minimal overhead, and it has gained wide popularity in IoT domains. For example, it has been employed for edge cloud lidar object detection by connecting AVs and infrastructure (Reiher et al., 2022) and real-time monitoring of connected vehicles (Sukmandhani and Zarlis, 2023). In the transportation domain, testbeds such as Mcity have demonstrated intersection management with autonomous vehicles in the physical world; however, these efforts have relied primarily on conventional V2X communication protocols (Naderian et al., 2024). Similarly, other field studies have focused on delivering awareness messages to vulnerable road users via LTE-V2X (Lusvarghi et al., 2023). However, the use of message broker-based control frameworks, such as RabbitMQ for intersection management, remains largely unexplored.

2.6 Research gap and contributions

Previous studies on V2X-based vehicular communication and intersection management have focused predominantly on simulation environments or constrained testbeds, overlooking critical aspects, including the scalability of the autonomous driving environment, as well as infrastructures, vehicles, and control data exchange. This limitation is particularly pronounced in existing research on intelligent intersections, where most coordination algorithms assume idealized infrastructure, low-latency communication, and fully autonomous agents. Moreover, standardized message sets such as SAE J2735 lack the flexibility to accommodate the dynamic and high-volume data required for emerging CAV services. As a result, the system's frequent updates often necessitate the implementation of inefficient workarounds or entirely new protocols.

To address these limitations, this study proposes a modular framework, mOS, which supports the plug-and-play integration of V2X communication modules, a real-time intersection management algorithm, and an MR-based testing environment. Physical-world application scenarios are implemented through an MR platform that enables bidirectional interaction between physical vehicles and virtual agents in real time. This finding demonstrates that the proposed framework is practical under physical world constraints, including communication latency, unpredictable human behavior, and infrastructure variability. This study not only demonstrates the feasibility of MR-integrated infrastructure guidance but also offers a new pathway for the scalable deployment and validation of CAV coordination systems in future innovative mobility ecosystems.

3 Methods

Our study proposes a plug-and-play mOS that leverages distributed edge computing, enabling the system to expand the spectrum of traffic information it can acquire and utilize in real time. This system is managed by an operator (Section 3.1) that is distributed across multiple central edge nodes and an expandable message set (Section 3.2). This approach links multiple edge devices into an mOS networking environment, including intelligent infrastructure (Section 3.3), connected vehicles (Section 3.4), and even a metaverse server for MR testing (Section 3.5), as illustrated in Fig. 1.

3.1 System orchestrator

The system orchestrator is the core component of architecture. It functions by processing reports of simulation events in real time, which correspond to specific automotive use cases. Its primary responsibilities include balancing the workload of mobility services within the system and coordinating communication among them. The orchestrator monitors the C-V2X network while analyzing actual data, simulated information, and system metrics to optimize current deployments.

To ensure that mobility systems operate efficiently, quickly, and reliably, the orchestrator dynamically adjusts runtime variables (e.g., resolution) and resource allocations (e.g., available memory) and determines which edge device should carry out the workload (Nguyen et al., 2025). The resulting deployment is continuously monitored and adapted to changes in the environment. Through the orchestrator, the distributed edge devices operate as a unified system, similar to modern cloud architectures, but with reduced network latency for users.

In addition, the architecture was designed for scalability and adaptability in more complex scenarios involving multiple vehicles and intersections. Built on Kubernetes, the system benefits from built-in horizontal scaling features that allow resources within each cluster to be rapidly adjusted to meet workload surges caused by dynamic traffic changes (e.g., sudden congestion at an intersection). A resource orchestration framework has also been implemented to dynamically balance computation between servers and vehicles, ensuring (1) that each service is provisioned with sufficient resources to avoid bottlenecks and (2) that network traffic is minimized through optimal task partitioning.

Furthermore, while intersections are designed to operate independently, they are capable of exchanging messages to coordinate intersection operations such as handover or computational offloading. In cases where an intersection becomes overloaded, a centralized controller determines which neighboring intersection can accept offloaded tasks to minimize network overhead. For heavily congested situations, however, a method of

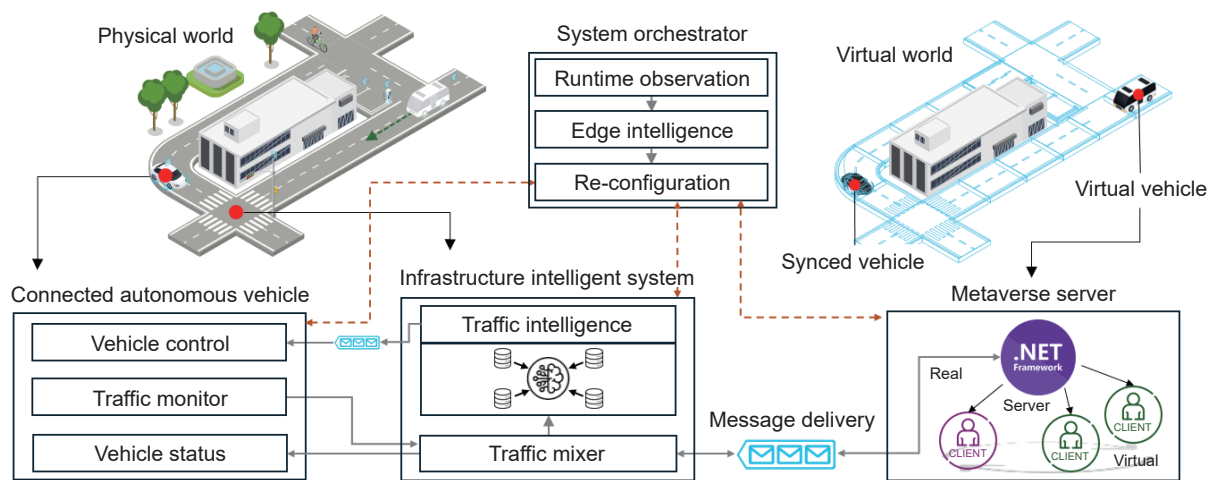


Fig. 1 Framework of mOS.

client selection is also necessary to maintain service quality, as not all vehicles require explicit control. Excluding low-risk vehicles from centralized management will be an important consideration for future work to address by the intelligence module.

3.2 Scalable distributed message delivery

The foundation of a system in the edge-cloud continuum is a fast and scalable messaging system, which is challenging to achieve owing to the rapidly changing nature of clients and the instability of networks, such as cellular connections. To address this, we utilize an extensible, minimal message set defined in a text-based serialization format, which includes a mandatory timestamp, ensuring lightweight and purpose-specific communication. This design supports customization for new components while minimizing latency. Each message begins with a timestamp, with all other fields tailored to the application, and can be represented in JSON or Protobuf for easy extension and efficient parsing.

The messaging system integrates both synchronous and asynchronous methods into a single hybrid protocol. Synchronous communication via gRPC uses compressed binary messages without field names for critical, real-time commands that require immediate acknowledgment, allowing for flexible use of cellular or PC5 interfaces. Asynchronous communication relies on RabbitMQ as a broker to handle periodic data, such as GPS updates, on a best-effort basis, thereby eliminating response overhead while managing message ordering and reordering for reliability. This distributed broker setup allows data to be sent to the nearest endpoint and forwarded efficiently to receiving services, adapting to varying network conditions while preserving the correct delivery order.

3.3 Infrastructure intelligence

Unlike other future mobility systems that focus solely on enhancing CAVs for decision-making, the proposed mOS actively incorporates infrastructure resources into real-time traffic planning and management. The system can optimize decision-making for each vehicle on the basis of the comprehensive data it has access to, whether via direct communication with CAVs or indirect identification of HVs.

For this framework, we implemented a variation of the well-established reservation-based AIM system (Dresner and Stone, 2008) that prioritizes safety while considering driver comfort. AIM coordinates entities within the intersection by allowing the direct reservation of space-time resources, ensuring collision avoidance. While AIM laid a strong foundation for reservation-based intersection management, there is room for improvement.

Our implementation enhances the traditional AIM by dynamically updating the requesting vehicle's maximum speed at each reservation request, thereby reducing stop delays and enabling more efficient intersection management.

Algorithm 1: Reservation-based intersection management

```

1  Entity  $k$  approaches the intersection
2  if Entity type = "CAV" then
3    if  $t_{k,\text{interval}} \geq t_{k,\text{threshold}}$  then
4      Vehicle sends to intelligence  $v_k, a_{k,\text{max}}, T_k, l_k, w_k$ 
5      Intelligence generates  $V_k$ 
6      Find space-time occupied from  $V_k, T_k$ 
7      Compare with existing reservations
8      if conflict with existing reservations then
9        Reject the reservation request
10        $v_{k,\text{max}} = v_{\text{red}}$ 
11     else
12       Accept the reservation request
13       Vehicle follows  $V_k$ 
14     end if
15   end if
16 else if Entity type = "HV" then
17   Find expected movement of incoming HV
18   Reserve space-time of lane for duration
19   Reset conflicting existing reservations of CAVs
20 end if
21 else if Entity type = "Pedestrian" then
22   Find expected crossing path of pedestrian
23   Reserve space-time of path for duration
24   Reset conflicting existing reservations of CAVs
25 end if
26 end if = 0

```

Note: The v_k is the current velocity of vehicle k , $a_{k,\text{max}}$ is the maximum acceleration of vehicle k , T_k is the trajectory of vehicle k , l_k is the length of vehicle k , w_k is the width of vehicle k , $t_{k,\text{interval}}$ is the reservation time interval, $t_{k,\text{threshold}}$ is a time interval threshold, and v_{red} is the velocity reduction. Constraint: The maximum acceleration and deceleration are limited to $\pm 4 \text{ m/s}^2$.

According to Algorithm 1, upon entering the control service zone of an intersection, a CAV k requests a reservation containing

its current state $(v_k, a_{k, \max}, l_k, w_k)$ and planned trajectory (T_k) . The intelligence algorithm then generates a velocity profile $V = \{v_{n1}, v_{n2}, \dots, v_{nT}\}$, taking into account its dimensions of length l_k and width w_k .

Intelligence then compares the requested space-time with all existing reservations to determine conflicts with existing reservations. If no conflict exists, the reservation is immediately accepted; then, the reserved vehicle crosses the intersection with its planned trajectory. However, if it is rejected, the vehicle must wait 0.5 s before retrying with adjusted parameters. The waiting mechanism, as suggested in the study by (Dresner and Stone, 2008), helps avoid excessive computation and prevents the intersection manager from being overloaded with unnecessary repeated requests. To minimize full stops and improve flow, the maximum speed $(v_{k, \max})$ of rejected vehicles is slightly reduced (v_{red}) , shifting their predicted trajectory in time and reducing overlap with other reservations while avoiding complex, computationally intensive path replanning.

Notably, when a CAV's reservation request is rejected, its state remains largely unchanged in subsequent requests. Since the vehicle has already moved as quickly as possible, subsequent trajectory predictions are affected primarily by noise and irregularities, making the new requests largely similar to previous requests. Upon rejection, the vehicle's maximum speed $(v_{k, \max})$ is reduced by a set value (v_{red}) , delaying its entry into the intersection by a small amount of time. This delay reduces the likelihood that the vehicle's trajectory will overlap with existing reservations. If reservations continue to be rejected, the vehicle may eventually reach a stop at the stop line. However, this method minimizes the number of instances where vehicles come to a complete stop.

For entities without communication capabilities, such as HVs and pedestrians, the system uses sensors to detect their presence and assigns space-time windows similar to traditional traffic signal phases. HVs receive lane-based green light intervals, requiring CAVs to reset any conflicting reservations and request access again. Pedestrian crossings are allocated fixed time windows, but to account for unpredictable behavior, such as jaywalking, the system includes safeguards. Any vehicle reservations overlapping with a detected pedestrian are reset, and vehicles in the intersection are instructed to slow down or stop until the crossing is clear.

3.4 Connected autonomous vehicles

CAV vehicles are integrated into mOS via a vehicle-in-the-loop approach, allowing them to interact with virtual objects or other vehicles approaching an intersection in an MR environment. The CAV receives information about surrounding objects from the infrastructure (traffic monitor in Fig. 1), which is then injected into the vehicle's perception system. Additionally, the CAV transmits its status (vehicle status in Fig. 1) to the infrastructure and can receive suggested speed recommendations (vehicle control in Fig. 1) to ensure safe and efficient intersection crossing. The vehicle connected to the mOS requires real-time message communication with the infrastructure, which is achieved through the message delivery protocol described in Section 3.2 and intersection crossing guidance provided by the intelligence algorithm in Section 3.3.

For safety reasons, a CAV cannot rely solely on control from the intelligence algorithm for the following reasons: (1) late transmission due to network bottlenecks and (2) outdated speed suggestions due to server bottlenecks. To ensure safety, the CAV verifies the real-time validity of the speed suggestion message by

comparing the timestamps. If collision risk conditions are detected in the control message, the vehicle overrides external inputs and engages its own control system to maintain operational safety.

3.5 Metaverse components

The metaverse, in mOS, plays a pivotal role in bridging the virtual and physical worlds. Virtual objects, such as vehicles and pedestrians, controlled by other clients are transmitted to actual vehicles through the Metaverse Server and System Orchestrator. This bidirectional communication allows actual and virtual objects to interact seamlessly within the MR environment.

To ensure the seamless interaction of mOS, we design a metaverse system architecture comprising a server for a scalable environment, a communication protocol for data transmission, and client entities for various types of client objects. The metaverse server facilitates the reception of data from physical world vehicles through RabbitMQ message queues, ensuring reliable and scalable communication. Outbound communications are managed via RabbitMQ fanout exchanges, allowing accurate representation of vehicle dynamics within the virtual space. Similarly, generated vehicle and pedestrian client data are transmitted from the metaverse server to RabbitMQ message queues, enabling physical-world vehicles to retrieve and interpret virtual object information in real time.

To ensure interoperability across platforms, the metaverse server converts coordinate data between the Unity coordinate system and the UTM frame and anchors the Unity local origin to a surveyed UTM point so that metric distances are preserved one-to-one. Positions received as east, north, and height are mapped to the Unity y-up world via a fixed-axis permutation and handedness correction, and geographic heading is translated to Unity yaw with wrap-around handling. A small, fixed offset between the GNSS antenna and the vehicle reference point is applied so that the rendered pose matches the physical body frame. For commands originating in the virtual world, the exact inverse mapping is applied so that actuation targets correspond exactly to what is visible in the scene.

To maintain safety under network variance, outbound commands to the CAV use a strict freshness window (TTL = 1.0 s); expired messages are not delivered. Real-vehicle messages are accepted only when the interarrival is < 1 s and the measured delay is 0–5 s; others are ignored as stale. All the messages carry NTP-synchronized timestamps, enabling end-to-end latency checks at each hop. On the metaverse client side, a two-step calibration process was carefully designed to bridge the missing samples (> 1.0 s) to increase the smoothness of the simulated real-vehicle motion. The first step used buffering and interpolation, following previous research, to align the data (Akenine-Moller et al., 2019; Kalman, 1960). The second step applies trajectory smoothing via a Kalman filter to address extended periods of data loss between actual and virtual object data communication, and excessive jumps trigger a filter reset to prevent visual/kinematic artifacts (Bishop and Welch, 2001; Maybeck, 1979). The orientation is smoothed with explicit limits on the pitch, roll, and angular speed to avoid jitter-induced oscillation. Together, these mechanisms maintain data integrity and real-time coherence between physical and virtual entities while preventing stale or erratic packets from influencing the control loop.

4 Proof of concept

To assess the effectiveness of the proposed mOS for infrastructure-guided operation, we conducted a comparative evaluation under vehicle-to-vehicle (V2V) and vehicle-to-pedestrian (V2P)

scenarios, both with and without mOS operation. This evaluation focuses on the adaptability of the plug-and-play concept in edge devices, including the intersection and the vehicle, via the mOS. In particular, we measured two key performance metrics: (1) driving behavior, which is an indicator of guidance application, and (2) communication latency, which is an indicator of real-time system responsiveness and safety. By comparing these metrics in the baseline and mOS-assisted conditions, we can determine how much intelligent infrastructure influences vehicle behavior.

4.1 Test environment

At unsignalized intersections where the distinction between major and minor roads is unclear, drivers typically follow the general right-of-way principle, known as the first-in, first-out rule (Li et al., 2023). However, this approach carries a high risk of collisions because of drivers' unclear interpretation of the right-of-way. Additionally, when multiple vehicles arrive at an intersection simultaneously, drivers often exhibit inconsistent decision-making regarding the right of way. To evaluate the mOS, which provides intersection crossing guidance through the reservation-based AIM system, we conducted experiments in a mixed-reality testbed located at the KAIST Munji campus, Daejeon, Republic of Korea. The testbed featured a four-leg intersection with a lane width of 3.5 m, meeting the Euro NCAP-recommended road width for safety evaluations. Additionally, the intersection is equipped with a fully controllable traffic signal box, which can be turned off to prevent unintended influences on vehicle behavior.

4.2 Scenario setup

The evaluation focuses on two key scenarios: V2V and V2P interactions. For the V2V interaction scenario, an actual CAV (white vehicle in Fig. 2a) drove a left turn from a designated starting point at a speed of 20 km/h. Moreover, a virtual vehicle (the blue vehicle driving at 20 km/h) crossed the intersection from right to left, following the dashed blue lane shown in Fig. 2a. To facilitate interaction at the intersection, the initial point and the desired speed of the CAV and HDV were predefined, with the CAV positioned 100 m away and the HDV positioned 150 m away from the center point of the intersection. For the intersection control based on the AIM system, the suggested speed range was defined as 30 m from the centroid of the intersection.

For the V2P interaction scenario, the car-to-pedestrian turning adult (CNBA) test, which is commonly used in Euro NCAP emergency braking system evaluations, was selected. In this scenario, the CAV made a left turn at 20 km/h, while a pedestrian

crossed the road at a constant speed from the nearest side. Unlike in the V2V interaction scenario, the pedestrian's speed was not strictly regulated, as an actual human participant walked in the MR test environment. Through these test scenarios, we demonstrated that mOS effectively managed complex interactions involving both autonomously controlled and human-controlled objects.

4.3 System implementation

To implement mOS, we developed a system architecture that integrates distributed edges, such as the system orchestrator, intelligence intersection edge, CAV, and virtual agents, in a synchronized environment, as shown in Fig. 3.

At startup, the orchestrator will receive a deployment request for diverse mobility services and deploy them within the system. During runtime, those will be monitored and updated as follows: First, it continuously collects network and resource metrics, as well as processed application data that do not contain private user information. Second, it employs intelligent orchestration algorithms to identify necessary deployment changes within the system (Nguyen et al., 2025). Finally, it instructs the devices to modify the deployed services accordingly. We leverage Kubernetes as our orchestrator because it provides a robust open-source framework for managing distributed workloads across edge devices. This ensures scalability, reliability, and efficiency. Kubernetes excels at managing containerized applications, enabling seamless deployment and updates in a plug-and-play manner. The system relies on a message broker with a publishing/subscribing architecture, enabling scalable, low-latency communication between components.

The upper level of the architecture shown in Fig. 3 coordinates interactions across multiple edge devices and the central orchestration system. As CAVs approach an intelligence intersection, their data are first routed through a vehicle router and local traffic module, which preprocesses local traffic information at the edge. The intelligence router at each edge device then exchanges these data with the main system, where the system orchestrator allocates resources and the metaverse router bridges real traffic data with virtual entities hosted on the metaverse server. This ensures that both actual vehicles and virtual agents share a unified, synchronized environment.

The lower-level architecture shows how individual vehicles and intersections operate. Each CAV transmits its current state as a *status_#1_Vn* message (e.g., position, velocity, and acceleration). A traffic router aggregates multiple incoming vehicle streams,

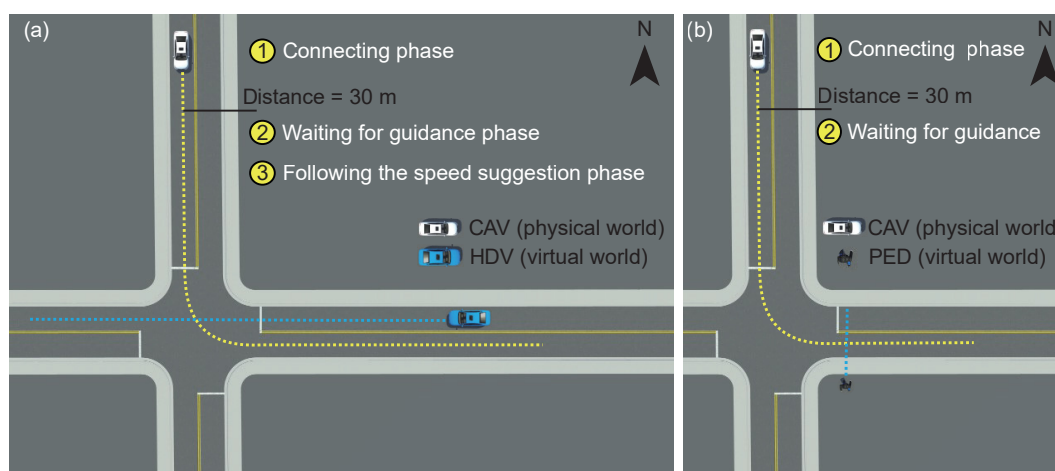


Fig. 2 Scenarios for proof of concept.

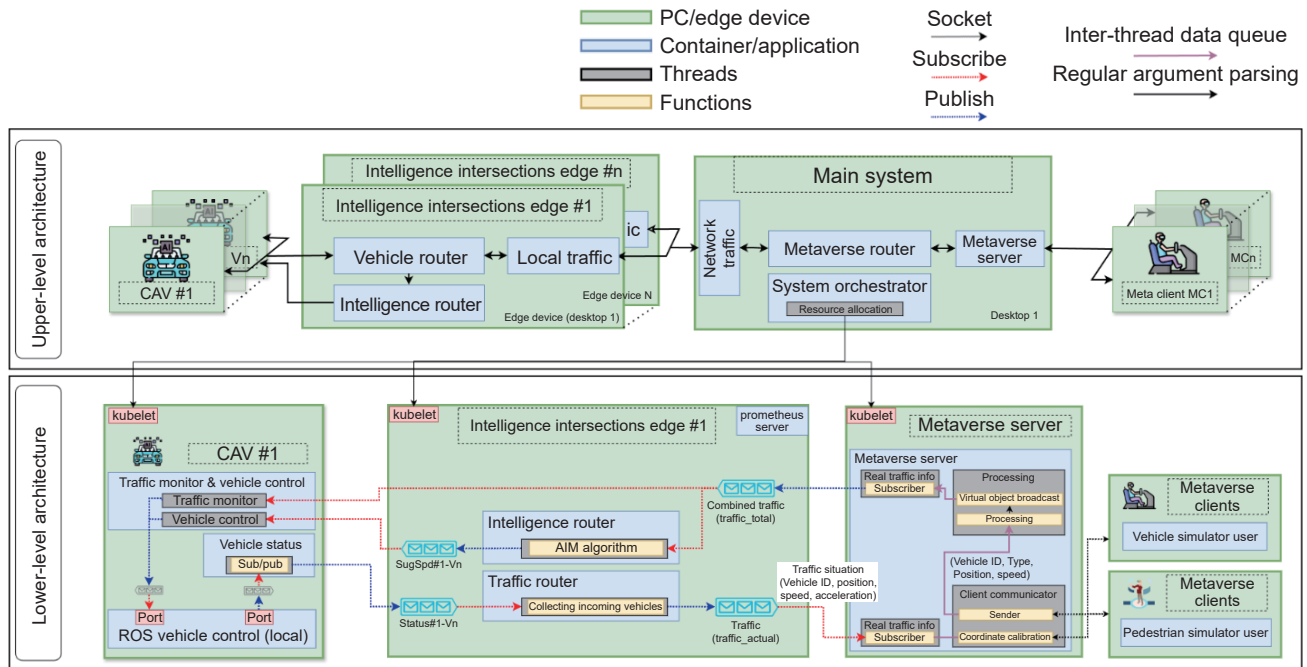


Fig. 3 mOS architecture for implementation.

converting them into combined traffic messages (*traffic_total*). These aggregated data streams are integrated with virtual objects, forming a mixed environment. The intelligence router within the AIM algorithm container subscribes to this traffic data stream, determines the intersection priority, and calculates a recommended speed for every timestamp of the CAV. The vehicle receiving this message, named *SugSpd_#1_Vn*, evaluated the suggested speed to determine whether following it would pose a collision risk to other road users. The recommended speed was approved if it was safe and sent to Apollo, the vehicle's internal control system (ROS), which adjusts the actuators via CAN/BUS communication. The message sets used in this architecture are provided in the Appendix.

In this study, the Hyundai Tucson Hybrid NX4 is utilized as a CAV for physical world experiments, as illustrated in Fig. 4a. Vehicle status data, such as position, velocity, and longitudinal

acceleration, can be collected directly from the vehicle or from the GNSS/IMU system. The vehicle's position is measured via a GNSS (Novatel PwrPak7) and a built-in IMU (Epson G320), both of which are enhanced with real-time kinematic (RTK) technology, for high navigation accuracy at 100 Hz with a 0.05 m deviation error. To enable high-bandwidth, low-latency communication between the CAV and the infrastructure, a 5G router is integrated into the system, as shown in Fig. 4b. This router facilitates real-time data exchange for cooperative driving and infrastructure-based speed recommendations, ensuring reliable connectivity even in dynamic urban environments.

The Apollo framework, shown in Fig. 4c, is used to merge the localization and perception systems and then plan the trajectory and control the vehicle autonomously. The basic safety mechanism operates according to the basic configuration of Apollo (Baidu Apollo team, 2017). Moreover, to control the

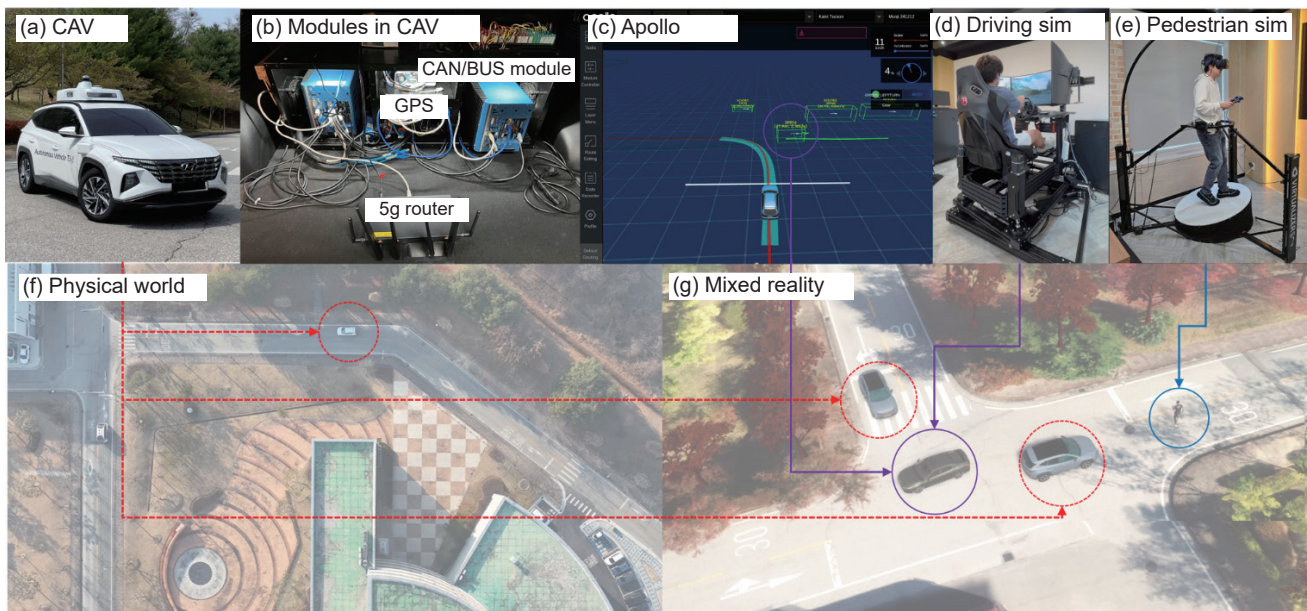


Fig. 4 Components of mOS.

vehicle according to the desired speed suggested by the infrastructure, the vanilla Apollo framework is modified to communicate with the infrastructure.

For the virtual vehicle, a 6-axis driving simulator was utilized, featuring a triple-monitor display and a physical steering wheel and pedal system to provide a realistic driving experience, as shown in Fig. 4d. Another virtual object, a pedestrian, was controlled by actual human participants wearing an HMD with a resolution of 4896×2448 pixels and a field of view (FoV) of 120° , as shown in Fig. 4e. This simulator accurately mapped pedestrian objects in the virtual environment while continuously tracking the position and orientation of their head. The vehicle and pedestrian movement data were transmitted to the edge server at a frequency of 100 Hz to represent the actions of vehicles and pedestrians in the MR environment. All collected data—whether from the actual vehicle, the virtual vehicle, or the virtual pedestrian—were processed at the edge server and presented in both the physical and virtual worlds, as shown in Figs. 4f and 4g, respectively.

5 Results

The study was conducted in a physical world testbed, where the mOS was deployed on each edge device, including the CAV, the intelligence infrastructure, and the metaverse server. Communication between these edge components enables the exchange of crucial information, such as position, velocity, and speed suggestions, to support the implementation of the MR

testbed. The message exchanged via the RabbitMQ message broker was collected under both conditions: with and without the mOS active.

The analysis of the study dataset was carried out in two main parts. First, the speed profiles of the vehicles were examined in relation to the effectiveness of the intersection crossing guidance provided by the mOS. Second, the analysis focused on the stability of each edge network, measuring the consistency and reliability of the system. This involved assessing the availability of CAV testing in the MR environment via the mOS.

5.1 Effect of the speed suggestion

As shown in Fig. 5a, the vehicle with speed suggestion drove at an average speed of 10 km/h when turning left, whereas the vehicle without speed suggestion (Fig. 5b) drove at speeds lower than 5 km/h in more than half of the trials and stopped in some trials. This is due to the potential risk of collision, which is determined by the embedded safety mechanism in Apollo.

Figs. 5c and 5d show the intersection between the vehicle and the pedestrian on the basis of the existence of a speed suggestion. The speed profile of a guided vehicle was more stable with lower variance than that of a nonguided vehicle. Compared with guidance, the collision prevention algorithm for nonguided vehicles delays decision-making when a pedestrian suddenly jaywalks. This delay led to sudden acceleration or urgent braking, resulting in the vehicle stopping in the middle of the path.

Table 1 presents the post encroachment time (PET) outcomes

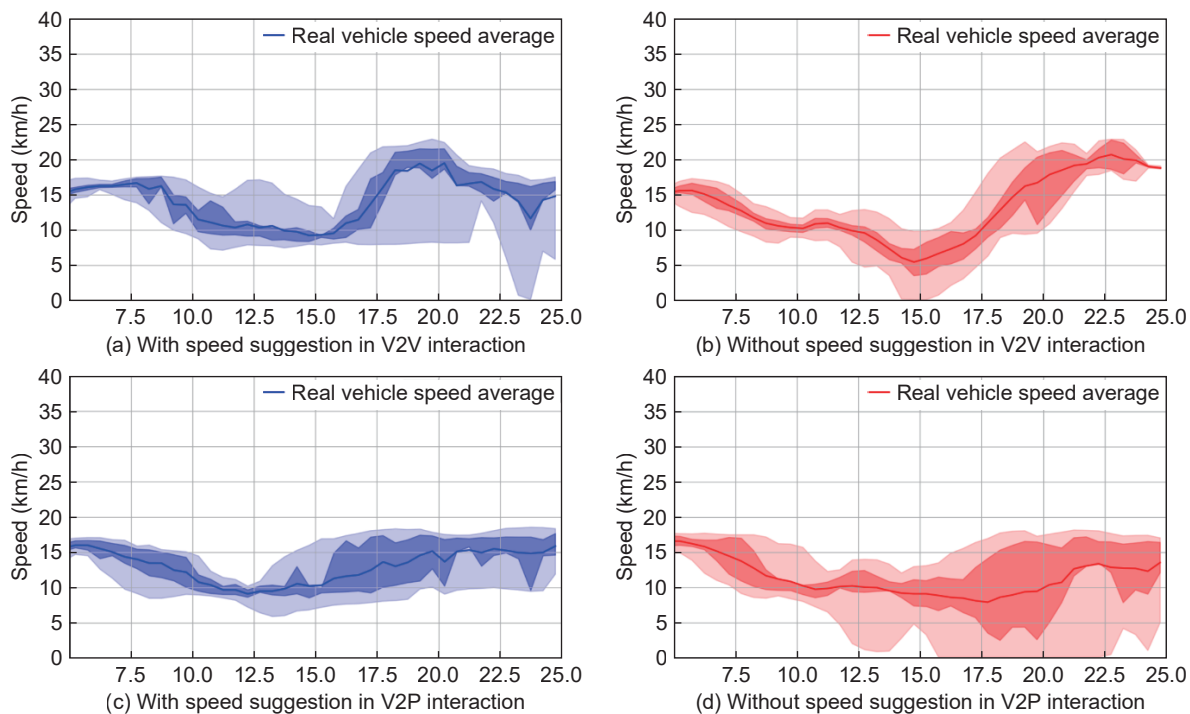


Fig. 5 Speed profiles of the actual vehicle depending on the scenario.

Table 1 Evaluation results of the post encroachment time

	Test scenario	Mean	Std	Min	Max	Q1	Q3
V2V	With speed suggestion	4.62	1.10	3.09	6.95	4.08	5.07
	Without speed suggestion	5.99	0.77	4.41	7.18	5.65	6.36
V2P	With speed suggestion	1.76	1.20	0.97	4.86	1.14	1.74
	Without speed suggestion	2.94	0.93	1.89	4.58	2.24	3.44

across the V2V and V2P scenarios with and without speed suggestions. In the V2V case, the mean PET decreased from 5.99 s (standard deviation (Std) = 0.77) in the baseline condition to 4.62 s (Std = 1.10) when speed suggestion was applied. This reduction indicates that vehicles were able to traverse the intersection with shorter temporal gaps, suggesting smoother and more coordinated interactions.

A similar pattern was observed in the V2P case, where the

mean PET decreased markedly from 2.94 s (Std = 0.93) without speed suggestion to 1.76 s (Std = 1.20) with speed suggestion. Notably, the standard deviation also decreased under the speed suggestion condition, implying that interactions became more stable and predictable, with fewer extreme PET values.

The results of comparing the time-space-speed trajectories during the scenario demonstration are shown in Fig. 6. When the CAV approaches the speed suggestion zone, the infrastructure

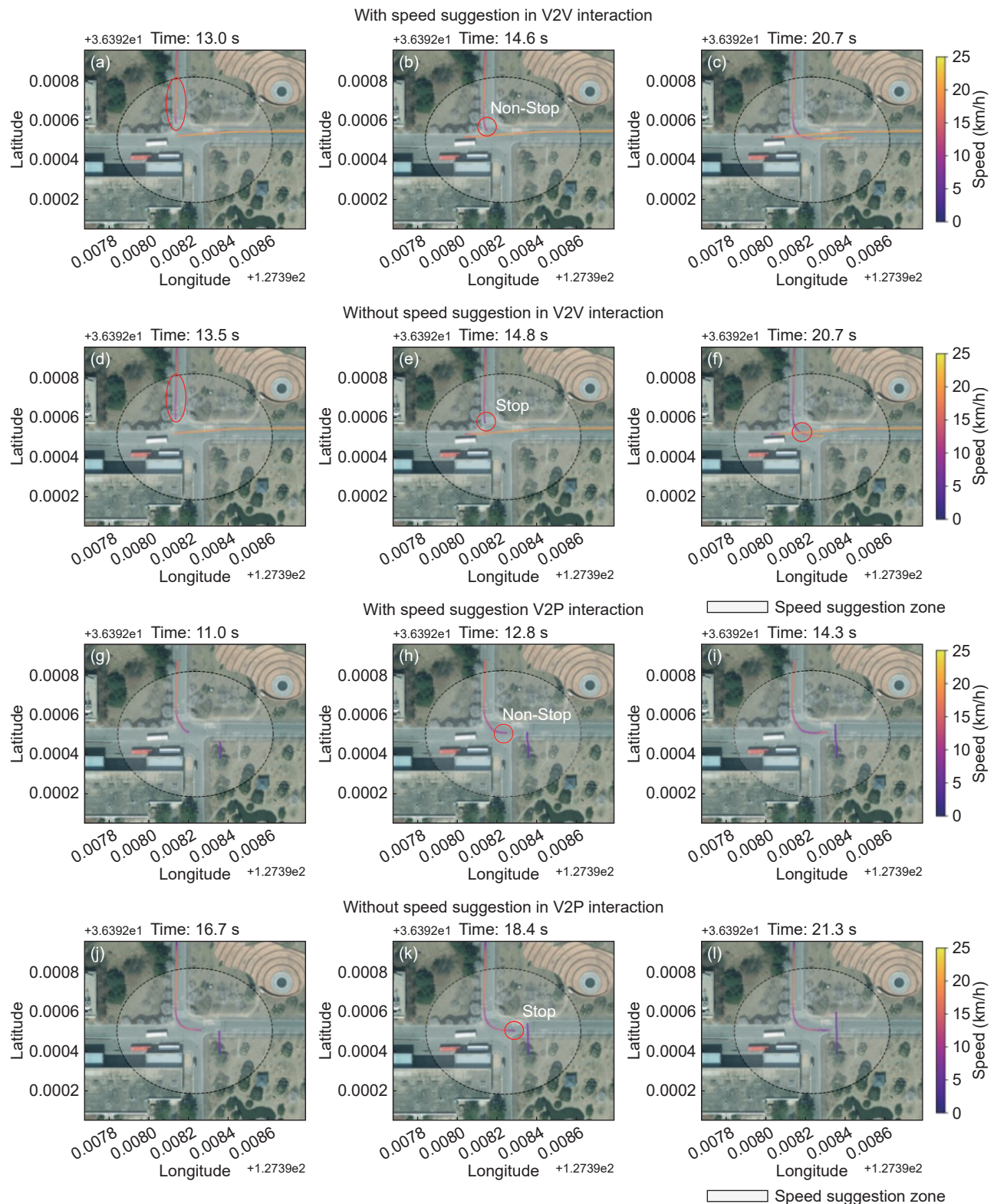


Fig. 6 Intersection trajectories based on the existence of speed suggestions.

determines the priority of approaching vehicles and provides speed suggestions. Therefore, the speed suggestion of the CAV managed its speed in advance (Fig. 6a) and passed the intersection without stopping (Fig. 6b) because it perceived that it would not collide with the virtual HV, even though the distance between the two vehicles was close due to the reservation algorithm. In contrast, without providing speed suggestions, the CAV decelerated far from the intersection (Fig. 6d), stopped avoiding a potential collision with the virtual HV (Fig. 6e) and reaccelerated only after the virtual HV had completely passed the intersection.

With respect to the vehicle-pedestrian interaction scenario, the vehicle's behavior clearly differed on the basis of whether a speed suggestion was present or absent. When the speed suggestion system was activated, the CAV adjusted its speed according to the speed suggestion provided upon entering the suggestion zone. Consequently, as shown in Fig. 6g, the CAV did not accelerate after completing the left turn, anticipating a pedestrian crossing. In contrast, when no speed suggestion was given, the behavior of the AV followed the typical "slow-in, fast-out" pattern during the left turn, as illustrated in Fig. 6j. It then stopped abruptly upon detecting a pedestrian crossing ahead, following the conservative collision avoidance algorithm, as shown in Fig. 6k. Therefore, providing speed suggestions from the mOS maintained safe intersection crossing without abrupt deceleration, resulting in smoother and more efficient maneuvering.

5.2 Effect of network communication

Since the proposed system is based on the C-V2X protocol, network performance metrics were collected during the trials. Given that the system delivers real-time vehicle positions and provides speed suggestions, achieving low latency is critical for ensuring timely and accurate information delivery. Furthermore, even if the average latency was low, consistency in communication delays was crucial. Therefore, jitter was also monitored to capture the variability in packet transmission times and to ensure stable system behavior.

Network communication performance was evaluated on the basis of the collected latency and jitter data during the field trials. According to the results summarized in Table 2, the mean latency was approximately 48.46 ms, with a standard deviation of 63.62 ms. The maximum latency observed during the trials was 479.39 ms. For jitters, the mean value was measured at 60.17 ms,

with a standard deviation of 53.46 ms. The maximum jitter observed was 754.50 ms, indicating that the stability of the communication link fluctuated significantly in some instances.

In addition, packet loss was analyzed to assess whether increasing vehicle speed could compromise data delivery reliability, and the results in Table 3 indicate consistently low loss rates across all speeds, confirming stable communication performance under dynamic driving conditions.

Overall, these results demonstrate that while the system generally maintains low average latency and jitter, supporting the real-time delivery of vehicle position and speed suggestion information, there are occasional peaks in delay and variation. Such spikes could compromise the stability of critical communications, especially in scenarios that require rapid reactions from vehicles or infrastructure. However, since the majority of the communication delays remained within an acceptable range, the proposed system was considered sufficiently reliable for real-time operations in the physical world. In addition, the packet loss rate did not significantly differ across varying vehicle speeds, indicating that stable service provision can be ensured even under dynamic driving conditions.

5.3 Effect of coordinating calibrations and synchronizations for mixed reality

To assess the effectiveness of the calibration and synchronization procedures, we conducted a quantitative evaluation using logged vehicle data under mixed-reality conditions. The analysis focused on residual errors after coordinate calibration and on the offsets introduced by trajectory smoothing, with the results summarized in Tables 4 and 5.

The calibration accuracy was evaluated by reapplying the deterministic mapping function to the physical world data and comparing the outputs with Unity-converted coordinates at identical timestamps. Since only samples with perfectly aligned timestamps were retained, timing mismatches are negligible, and the remaining error reflects only static bias and sensor noise. As shown in Table 4, the resulting position errors remained within a few meters (mean 0.117 m), whereas the heading errors were effectively zero. These residuals are consistent with the centimeter-level baseline accuracy provided by the RTK-aided GNSS/IMU, indicating that the calibration does not yield meaningful additional errors.

Table 2 Evaluation results of latency and jitter

Measurement	Latency (ms)			Jitter (ms)		
	V2V	V2P	Mean	V2V	V2P	Mean
Mean	42.05	54.87	48.46	60.61	59.73	60.17
Std	49.02	78.21	63.62	53.61	53.30	53.46
Min	8.00	1.00	4.50	1.00	1.00	1.00
Max	459.02	499.75	479.39	745.00	764.00	754.50

Table 3 Percentage of packet loss (%) according to the approaching speed

CAV speed (km/h)	Mean	Std	Min	Q1	Q3	Max
20	0.201	0.184	0.000	0.000	0.344	0.347
30	0.171	0.235	0.000	0.000	0.402	0.452
40	0.106	0.238	0.000	0.000	0.000	0.532
50	0.285	0.344	0.000	0.092	0.477	0.569

Table 4 Numerical errors in the coordinate calibration and synchronization process

Test scenario		Position error		Heading error	
		Mean (m)	Variance (m ²)	Mean (°)	Variance ((°) ²)
V2V	With speed suggestion	0.091	0.0011	0.000 133	0.000 027
	Without speed suggestion	0.093	0.0013	0.000 001	0.000 000
V2P	With speed suggestion	0.147	0.0032	0.000 000	0.000 000
	Without speed suggestion	0.111	0.0033	0.000 000	0.000 000
Average		0.117	0.0022	0.000 045	0.000 007

Table 5 Numerical errors in the trajectory smoothing process

Test scenario		Position error			Heading error		
		Mean (m)	Variance (m ²)	Drift (m/s)	Mean (°)	Variance ((°) ²)	Drift ((°)/s)
V2V	With speed suggestion	0.935	0.437	0.0113	0.117	0.113	−0.009
	Without speed suggestion	0.477	0.067	0.0045	0.065	0.012	−0.011
V2P	With speed suggestion	0.979	0.412	0.0086	0.128	0.065	−0.004
	Without speed suggestion	0.494	0.087	−0.0065	0.062	0.014	−0.001
Average		0.721	0.251	0.0045	0.093	0.051	−0.006

When trajectory smoothing was applied for synchronization, larger offsets were observed, which is expected when visually stable avatar motion is prioritized over strictly lag-free tracking. Table 5 shows that the mean position error was 0.721 m, corresponding to submeter- to meter-level horizontal shifts. The value of drift is 0.0045 m/s for the position heading and approximately −0.006 (°)/s for the heading. These drift rates amount to only a few centimeters of position error and fractions of a degree of heading error, indicating that smoothing affects mainly instantaneous offsets rather than long-term accuracy. Furthermore, when speed suggestions were provided by the intelligence algorithm, the prediction of the positions of actual vehicles in the virtual environment on the basis of prior vehicle data resulted in larger position errors than those in cases without speed suggestions.

6 Discussion

The key finding of this study lies in the successful implementation and validation of the proposed plug-and-play mOS framework in a physical world environment. The containerized edge nodes, orchestrated via Kubernetes, were connected to an intelligence edge server deployed at an actual intersection, a CAV, and a metaverse server. This setup enabled the testing of intersection-passing scenarios involving interactions between real vehicles and virtual entities such as vehicles and pedestrians. It represents an innovative case where a variety of independent technologies—including actual and virtual vehicles, pedestrians, intelligent control modules, and communication networks—were integrated and demonstrated within a unified MR environment.

While the existing J2735-standard-based message structure offers advantages in terms of communication efficiency, it presents several limitations when applied to the implementation of complex services required by evolving CAV technologies. To address this, this study proposes an extensible message set that allows the infrastructure to evaluate vehicle priority at intersections and transmit speed advisory messages to facilitate safe passages. According to the literature, the J2735-compliant structure requires a response time of approximately 100 ms, as data are exchanged

between vehicles every 100 ms (Khan et al., 2021). The average 100 ms observed in this study met that standard, suggesting that the transition from a binary to a more flexible XML-based message structure does not compromise real-time traffic control performance. Furthermore, the proposed message set supports scalability toward intelligent services and provides structural advantages in accommodating complex traffic scenarios. Additionally, the service availability rate was analyzed through packet loss measurements during the experiments, with an average of 0.201% and a standard deviation of 0.184, as shown in Table 3. According to an existing study by (Kutilla et al., 2021), the V2V packet loss rate under 5G environments was reported as zero regardless of packet size, and while the observed values in this study were slightly higher, they remained within a negligible range. Moreover, the results revealed no significant variation in packet loss across different vehicle speeds, confirming that the proposed system can provide stable communication performance even under dynamic driving conditions.

To validate these capabilities, an intelligent vehicle control algorithm, AIM, was applied in the context of unsignalized intersections, where the system dynamically determines the crossing order of approaching vehicles in real time following the first-come first-serve policy. The algorithm leverages computational resources on the intersection edge server to enable localized, safe, and efficient intersection operations, and its effectiveness is demonstrated under physical world conditions. However, excessive deceleration can potentially degrade throughput because of consecutive rejections of multiple approaching vehicles. To address this, the proposed mechanism prevents vehicles from arriving at a complete stop by assigning alternative trajectories to approaching vehicles, thereby avoiding overlap in the conflict zone. Consequently, our approach is expected to enhance both the intersection flow and the overall throughput.

In addition, although the safety level during intersection crossing can be enhanced through more advanced control algorithms for individual vehicles, such improvements are vehicle-specific and present challenges for achieving network-wide optimization. Moreover, if different manufacturers apply

heterogeneous safety algorithms at the same intersection, the lack of mutual understanding between vehicles may result in unnecessary stops, confusion, and even collisions. Therefore, in scenarios such as intersection crossing, implementing control algorithms that are optimized for local traffic characteristics is more effective. This demonstration thus constitutes a significant advancement beyond conventional simulation-based approaches, as it validates such logic in a physical world road environment.

The structural characteristics of the plug-and-play system also enhance its scalability and flexibility. The addition or removal of edge nodes allows for various system configurations. In cases where infrastructure sensors were absent, interactions were implemented via virtual entities. Virtual vehicle data generated by a simulator were transmitted to the edge server and subsequently forwarded to the CAV perception module via a message broker. This mechanism allows the actual vehicle to receive traffic information beyond its sensor range, even in the absence of sensors from the physical infrastructure. Furthermore, integration with the metaverse environment enables highly realistic interactions with multiple objects, including vehicles and pedestrians.

Additionally, the AI module within the proposed framework is modularized in an independent, container-based architecture. This design enables seamless replacement or expansion of various intersection control strategies beyond the algorithm demonstrated in this study. Compared with traditional microscopic simulation-based approaches, the proposed system significantly enhances realism and provides a practical alternative for the safe validation of complex and high-risk traffic scenarios.

The experimental results demonstrated that the intelligent algorithm successfully analyzed virtual vehicle information and injected it into an actual vehicle in real time, providing speed advisories to facilitate safe traversal through unsignalized intersections. A behavioral analysis revealed that without the algorithm, the actual vehicle exhibited delayed perception responses, treating the situation as hazardous and arriving at a stop. This suggests that the default safety mechanisms of CAVs, while conservative, may inadvertently reduce intersection efficiency. In contrast, the introduction of speed suggestions allows vehicles to drive the intersection without stopping, thereby improving the overall operational efficiency. Moreover, overly aggressive speed control aimed solely at maximizing efficiency could compromise safety. According to this knowledge, the value of PET after the suggestion in our demonstration was observed to decrease. However, the observed PET values under the speed suggestion condition remained above the threshold, which is 1.0 s, indicating that intersection operations were not compromised in terms of safety according to the study by (Paul and Ghosh, 2020). Therefore, the proposed approach demonstrates that safe intersection passages can be achieved through speed control, striking a balance between efficiency and safety.

Finally, certain limitations in the communication environment were observed. The experiment utilized a commercial 5G router instead of a dedicated C-V2X network, which resulted in relatively high latency and inconsistent jitter. However, existing references indicate that these conditions remain within acceptable thresholds, and significant improvements are expected in future applications using dedicated C-V2X infrastructure. Despite these limitations, the study successfully demonstrated the scalability and physical world applicability of the proposed plug-and-play testbed framework.

7 Conclusions

As autonomous driving technology advances toward commercialization, real-time interaction between vehicles and infrastructure is emerging as a crucial factor in ensuring traffic efficiency and safety. However, current V2X systems focus heavily on the communication layer and lack sufficient intelligence at the infrastructure level to respond adaptively to the complexity of physical world traffic scenarios. In particular, unsignalized intersections, nonconnected entities, and heterogeneous road users present challenges that existing message structures and decision algorithms are not fully equipped to handle.

To address these issues, this study proposed a modular, edge-intelligence-based mOS and validated it through actual intersection deployments and metaverse-integrated MR simulation environments. The proposed framework, built on a containerized architecture and an extensible message structure, demonstrated flexibility in supporting a variety of decision-making algorithms and communication protocols. By enabling interaction between physical vehicles and virtual objects, the testbed facilitated the safe and repeatable evaluation of high-risk intersection scenarios, as well as the quantitative assessment of algorithm effectiveness.

The results show that the system successfully overcomes the limitations of the existing J2735-based binary message structure while maintaining real-time performance. The intelligent control algorithm applied to unsignalized intersections was shown to produce meaningful improvements in vehicle behavior control. Additionally, the use of virtual object injection in sensor-limited environments and the integration of metaverse-based experiments reduced both cost and safety risks, offering a practical platform for advanced testing.

Although the study was conducted using a commercial 5G network rather than a dedicated C-V2X infrastructure, the observed latency and jitter were within acceptable thresholds. It is expected that future deployment using dedicated C-V2X networks will further enhance system stability and precision. Furthermore, to more rigorously validate the effectiveness of the proposed framework, a direct comparative evaluation against existing V2X systems will be an important direction for future research. In conclusion, this research presented a novel intersection management model that integrates intelligent infrastructure design, flexible message architecture, and virtual-real experimental platforms.

In the future, this research could further enhance the proposed framework by integrating more diverse physical world traffic conditions, including multimodal environments involving micromobility and public transport. Furthermore, scaling the system to scenarios with multiple vehicles and multiple intersections is crucial in the next step. This involves not only managing local intersection dynamics but also coordinating inter-intersection communication and offloading strategies to ensure balanced computation and optimized traffic flow across a broader network. Additionally, the integration of predictive behavior models and reinforcement learning-based decision algorithms at the infrastructure level could enhance the adaptability of intersection management under highly dynamic or congested conditions. This would help evaluate interoperability, network load distribution, and scalability in actual urban mobility ecosystems.

Appendix

Table A1 Standard messageset modification

J2735, BSM core data			This study		
Field name	Description	Type	Field name	Description	Type
Id	TempID	String	Id	TempID	Int
secMark	Millisecond	Int	Timestamp	Millisecond	Int
lat	Latitude	Int	lat	Latitude	Int
long	Longitude	Int	long	Longitude	Int
elev	Elevation	Int	elev	Elevation	Int
speed	Speed	Int	speed	Speed	Float
heading	Heading	Int	heading	Heading	Float
size	VehicleSize(width/length)	Int	size	VehicleSize(width/length/height)	Float
msgCnt	Message count	Int	—	—	—
angle	SteeringWheelAngle	Int	—	—	—
transmission	TransmissionState	Enumerated	—	—	—
accelSet	AccelerationSet4Way	Sequence	—	—	—
brakes	BrakeSystemStatus	Sequence	—	—	—
accuracy	PositionalAccuracy	Sequence	—	—	—
—	—	—	cType	Actual or virtual objects	String
—	—	—	accMax	Maximum acceleration	Float
—	—	—	sgspeed	Suggested speed	Float

Replication and data sharing

The code and dataset for our proposed model have been uploaded to ETS-Data. For further details, please refer to <https://doi.org/10.26599/ETSD.2025.9190063>.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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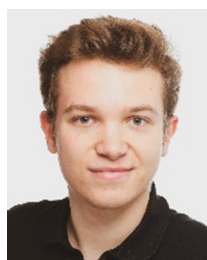
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