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Article

Keywords: Aware Communication, Semantic Edge Intelligence, 6G Vehicular Networks, UAV Communication, Semantic Communication, Edge AI, Multi-Agent Coordination, Adaptive Routing, Human-in-the-Loop, Semantic Security

Posted Date: June 30th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9990389/v1

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Additional Declarations: No competing interests reported.

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Abstract: *Autonomous UAV–vehicular communication in 6G environments requires low-latency, context-aware, and scalable edge intelligence beyond conventional data-centric transmission models. This paper proposes SEM-EDGE-X, an intent-aware semantic edge intelligence framework that integrates semantic feature extraction, adaptive edge routing, predictive resource allocation, and multi-agent coordination for dynamic UAV–vehicular networks. The framework incorporates cold-start semantic fusion, uncertainty-aware human-in-the-loop reinforcement, semantic conflict resolution, and trust-driven security mechanisms to improve communication reliability and decision efficiency. SEM-EDGE-X is evaluated using a MATLAB/Python-based simulation environment with SUMO mobility modelling, KITTI and UAVDT datasets, and CNN-based semantic encoding under varying UAV and vehicular densities. Performance is analyzed using latency, semantic accuracy, semantic similarity, energy consumption, throughput, scalability, and SNR robustness metrics. Experimental results demonstrate that SEM-EDGE-X consistently outperforms conventional cloud, MEC, DeepSC, and AI-assisted edge frameworks in highly dynamic 6G communication environments*

Keywords: *Aware Communication, Semantic Edge Intelligence, 6G Vehicular Networks, UAV Communication, Semantic Communication, Edge AI, Multi-Agent Coordination, Adaptive Routing, Human-in-the-Loop, Semantic Security.*

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1. Introduction

1.1. Motivation and research gap

The rapid evolution of 6G communication technologies is expected to support ultra-low latency, high-speed data transmission, and intelligent network coordination for autonomous systems operating in highly dynamic environments. The impact these innovations will have on unmanned aerial vehicles (UAVs), intelligent transportation systems, and autonomous vehicular networks is substantial as they rely on continuous sensor systems and real-time communications to provide reliable access to mobile devices. A major concern regarding the large-scale implementation of UAV-to-vehicle (UAV–vehicular) networks relates to the tremendous amounts of heterogeneous sensory and mobility data generated by such networks.

This presents significant challenges, including increased communication congestion, increased communication latency, low bandwidth utilization, and excessive computational demand on all devices involved in the communication network.

Current communication architecture primarily uses data-oriented transmission methods that transmit complete raw data regardless of the degree of contextual significance attached to the data being transmitted. By employing current methods, redundant communication is created, which ultimately decreases the efficiency of making decisions in time-critical environments because they will take longer to complete. However, new advances in Semantic Edge Intelligence (SEI) created by combining semantic communications, edge AI, and 6G networking have demonstrated how to increase communication efficiency by only transmitting the contextually relevant aspects of data instead of transmitting all of that data. Semantic processing allows for a reduction of unnecessary transmission overhead, will improve the resource allocation of all devices involved in the communication network, and will increase the speed with which decisions can be made in intelligent mobility environments.

Existing semantic communications frameworks have progressed tremendously in meeting the demands of isolated vehicle-to-vehicle (V2V) and vehicle-to-UAV (V2U) use cases, however, they still do not provide support for coordinated semantic intent-based communication, adaptive-edge routing of data, predictive resource allocation or cooperative multi-agent intelligence within rapidly changing 6G environments. Current semantic communications solutions also do not align on integrating semantic priority, uncertainty-aware human intervention, conflict-aware cooperation, semantic security and distributed-edge intelligence into one framework. This lack of unified solutions to these challenges limits the scalability, adaptability and reliability of communication in high-density mobility and variable wireless conditions.

In response to these challenges, we propose SEM-EDGE-X, an intent-based semantic edge intelligence framework for the use in UAV vehicular operating networks (6G). The SEM-EDGE-X framework integrates: semantic feature extraction; semantic-aware routing; adaptive-edge coordination; predictive resource scheduling; multi-agent conflict resolution; and trust-aware semantic security into a single platform. The performance of the SEM-EDGE-X framework is evaluated via simulations in the MATLAB/Python environment with SUMO mobility modelling, KITTI and UAVDT datasets with two CNN-based methods of semantic encoding to show the scalability of the platform, SNR robustness, and optimal handover conditions for variable mobility scenarios (6G).

1.2. Key Contributions

The major contributions of this work are summarized as follows:

1. The first major contribution of this research is the development of SEM-EDGE-X, which is a single framework applying the semantic definition of "intention" to provide UAV-vehicle communications within the 6G environment.
2. The second major contribution is the introduction of a task-adaptive semantic communication mechanism that can be utilized to determine the importance of content and minimize unnecessary transmitted information.
3. A semantic-aware adaptive routing and predictive resource allocation strategy is developed to minimize latency, improve throughput, and optimize edge resource utilization.
4. A weighted multi-agent conflict resolution mechanism is designed to support cooperative semantic coordination in dense UAV–vehicular deployments.
5. An adaptive cold-start semantic fusion model is incorporated to improve semantic representation stability during initial deployment stages.
6. A Human-in-the-Loop (HITL) semantic reinforcement mechanism is integrated to support uncertainty-aware decision-making in safety-critical conditions.
7. A semantic trust and anomaly-aware security layer is proposed to improve resilience against malicious or unreliable semantic information.

Extensive simulations are conducted under varying UAV densities, vehicular mobility conditions, SNR levels, and network scales using KITTI, UAVDT, and SUMO-based environments. Experimental results demonstrate that SEM-EDGE-X outperforms conventional cloud, MEC, DeepSC, and AI-assisted edge communication frameworks in terms of latency, semantic accuracy, semantic similarity, throughput, scalability, and energy efficiency.

1.3. Research Objectives

The primary objective of this research is to develop a scalable and intelligent semantic edge communication framework capable of supporting real-time UAV–vehicular coordination in next-generation 6G environments. The proposed work aims to integrate semantic communication, edge intelligence, adaptive routing, and predictive resource optimization to improve communication efficiency, semantic reliability, and decision-making performance under highly dynamic mobility conditions. Furthermore, this research seeks to enhance robustness against wireless channel degradation, dense network congestion, and mobility-induced handover interruptions while maintaining low latency, high semantic preservation, and efficient energy utilization in autonomous aerial and vehicular communication systems

2. Related Work

2.1. Taxonomy of semantic-aware edge frameworks

Recent progress in 6G technology reflects the move from traditional designs (i.e., communication based on bits) toward new ways of designing communication systems based on meaning, intention, and purpose using different semantic-based communication methods [4], [13]. Semantic communication combined with edge intelligence enables autonomous vehicles (AVs) and unmanned aerial vehicles (UAVs) to perform context-aware processing with lower latency and improved bandwidth efficiency [18], [21].

Several studies have explored semantic-aware architectures for intelligent transportation and UAV-assisted communication systems. Ji [9] and Wang et al. [17] discussed semantic communication mechanisms for 6G environments using AI-driven semantic encoding and adaptive transmission strategies. Similarly, Feng et al. [6] introduced AI-native semantic edge paradigms for distributed edge intelligence, while Ogenyi et al. [12] reviewed semantic-aware 6G frameworks integrating edge computing and intelligent networking.
In UAV-assisted environments, semantic-aware handover and optimization approaches have been investigated to improve mobility support and communication reliability [2], [25]. Song et al. [14] proposed a knowledge graph-driven UAV cognitive semantic communication framework for efficient object detection, whereas Haider et al. [7] integrated blockchain-assisted semantic aggregation for secure UAV-enabled Internet of Vehicles (IoV) systems.
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Despite these developments, most existing frameworks focus on isolated semantic transmission or edge optimization independently. Current systems rarely provide unified support for intent-aware semantic coordination, predictive edge orchestration, adaptive resource allocation, conflict-aware multi-agent collaboration, and human-in-the-loop (HITL) decision support in highly dynamic UAV–vehicular 6G environment.

2.2. Comparative Analysis of Existing Frameworks

Table 1. Comparative Analysis of Existing Semantic-Aware Edge Frameworks

Study	Focus Area	Techniques Applied	Major Limitation
Haider et al. (2026)	UAV-assisted IoV semantic aggregation	Edge AI + blockchain	No conflict-aware coordination or HITL integration. https://doi.org/10.1016/j.jnlest.2026.100350
Wang et al. (2025)	Semantic-enabled 6G communication	AI-driven semantic resource allocation	High computational complexity. https://doi.org/10.1109/ACCESS.2025.3532797
Zhang et al. (2025)	Semantic edge computing	Integrated semantic networking	Privacy and deployment overhead. https://doi.org/10.1016/j.comnet.2025.111531
Ji (2025)	Semantic communication frameworks	Semantic encoding and decoding	Scalability challenges. https://doi.org/10.54097/vwsfa141
Ahmad et al. (2024)	MEC service migration	Deep reinforcement learning	High state-processing complexity. https://doi.org/10.1109/OJCOMS.2024.3443514

Lokumarambage et al. (2023)	Semantic image transmission	Deep semantic compression	Sensitive to noisy wireless channels. https://doi.org/10.1109/ACCESS.2023.3266656
Zheng et al. (2025)	IRS/UAV-enabled MEC optimization	Semantic-aware intelligent optimization	Limited semantic coordination support. https://doi.org/10.1186/s13638-025-02478-5
Al Hameed et al. (2025)	UAV semantic handover	Semantic-aware edge intelligence	Lack of cross-layer orchestration. https://doi.org/10.48550/arXiv.2509.22668

Table 1 shows that existing studies mainly concentrate on semantic transmission, mobility optimization, or edge resource management as separate research directions. However, unified semantic intelligence architectures capable of jointly handling communication, computation, mobility, security, and cooperative decision-making remain limited.

2.3. Positioning of SEM-EDGE-X

Existing semantic communication frameworks such as DeepSC and JSCC primarily emphasize semantic encoding and reconstruction for end-to-end transmission. Edge AI and MEC systems focus on computation offloading and resource allocation without incorporating semantic intent awareness. Likewise, HITL systems provide assisted decision-making but lack integration with semantic communication and adaptive edge orchestration.

To address the problems posed by semantic communication limitations, the SEM-EDGE-X framework integrates multiple concepts for providing UAV-vehicle communications, including: (a) semantic feature extraction; (b) adaptive semantic routing; (c) predictively allocated resource allocation; (d) cold start semantic adaptation; (e) multi-agent conflict resolution; (f) semantic trust assessment and HITL-driven decision reinforcement; (g) consistency with all top-down layers within a single framework.

Table 2. Positioning of SEM-EDGE-X Against Existing Frameworks

Capability	Existing Semantic Frameworks	Edge AI/MEC Systems	HITL Systems	SEM-EDGE-X
Semantic-aware communication	Partial	Limited	No	Yes
Edge-aware semantic routing	No	Partial	No	Yes
Multi-agent UAV–vehicle coordination	No	Limited	No	Yes
Predictive resource allocation	No	Partial	No	Yes
Cold-start semantic adaptation	No	No	No	Yes
Human-in-the-loop integration	No	No	Partial	Yes
Semantic trust and anomaly handling	Limited	Partial	No	Yes
Cross-layer optimization	No	Partial	No	Yes

Table 2 indicates that, unlike current frameworks, which focus on optimizing separate communication or computation processes, SEM-EDGE-X integrates multiple parts of all layers of communication, edge intelligence, resource management and collaborative decision-making processes through unified semantic orchestration.

2.4. Research Gap

In recent years, both semantic communication and edge intelligence have received substantial attention; however, there are support gaps that exist for UAV-vehicular 6G systems. Most frameworks today continue

to concentrate on the efficiency of a semantic transmission; however, cooperative reasoning for semantics between two or more autonomous agents travelling at high speed and have no means in which to communicate directly is not addressed. Additionally, they typically do not include adaptive priority levels for semantics, predictive energy-aware scheduling for edge-based nodes and/or devices, nor do they allow for data-driven or strategically planned modes of transportation in terms of traffic and/or motion metrics.

The lack of human intervention mechanisms that consider uncertainty when deciding, i.e., a "safety-critical" environment, for providing semantic communication in many of today's systems is generally underdeveloped. Additionally, there have only been a small number of studies that have examined semantic validation that incorporate security measures against unauthorized access and trust-based semantics filtering mechanisms in the context of distributed UAV-vehicular edge systems. There has also been limited work done to date with respect to optimizing the integration of communication systems, edge computing, mobility management and intelligent orchestration of resources across all layers of a unified system.

To help address the stated gaps, and provide solutions, the proposed SEM-EDGE-X framework provides an Integrated Semantic Edge Intelligence Architecture for combining: intent aware semantic communication; adaptive edge-based coordination; predictive resource allocation; conflict aware collaboration between multi-agent systems; enforcement of semantic security; and the use of HITL-assisted decision support mechanisms through Semantic Communications for autonomous 6G environments.

3. System model and problem formulation

3.1. SEM-EDGE-X Network Architecture

The SEM-EDGE-X framework is designed as a three-layer semantic edge intelligence architecture for UAV–vehicular 6G communication environments. The architecture consists of:
(i) the sensing layer,
(ii) the semantic edge layer, and
(iii) the intelligent 6G coordination layer.

At the sensing layer, autonomous vehicles and UAVs continuously generate heterogeneous data streams including images, telemetry information, mobility traces, environmental observations, and navigation parameters through onboard sensors. Instead of transmitting complete raw sensor streams, SEM-EDGE-X performs semantic-aware filtering to extract only contextually meaningful information relevant to the target task.

The semantic edge layer performs semantic feature extraction, semantic prioritization, adaptive edge selection, and semantic-aware routing using distributed edge servers. A lightweight CNN-based semantic encoder is employed to identify task-relevant semantic representations before transmission. Unlike conventional fixed semantic encoders, the proposed framework adopts a task-adaptive semantic encoding mechanism where feature extraction is dynamically conditioned on the target semantic objective.

Let τ_k denote the semantic task label associated with application k. The task label is transformed into a lightweight task embedding vector and fused with the semantic encoder to prioritize context-specific semantic features. This enables adaptive semantic representation for heterogeneous applications such as autonomous navigation, cooperative sensing, object detection, and intelligent mobility coordination.

As illustrated in Figure 1, the intelligent 6G coordination layer manages semantic routing, distributed edge synchronization, predictive resource scheduling, and semantic-aware communication orchestration. The complete SEM-EDGE-X workflow operates through seven major stages:

1. Semantic feature extraction
2. Semantic significance evaluation
3. Adaptive edge node selection
4. Collaborative semantic synchronization
5. Semantic-aware routing
6. Predictive resource scheduling
7. Energy-aware feedback optimization

This layered semantic architecture reduces unnecessary communication overhead while improving

semantic relevance, latency performance, throughput, and energy efficiency in dynamic UAV–vehicular 6G ecosystems.

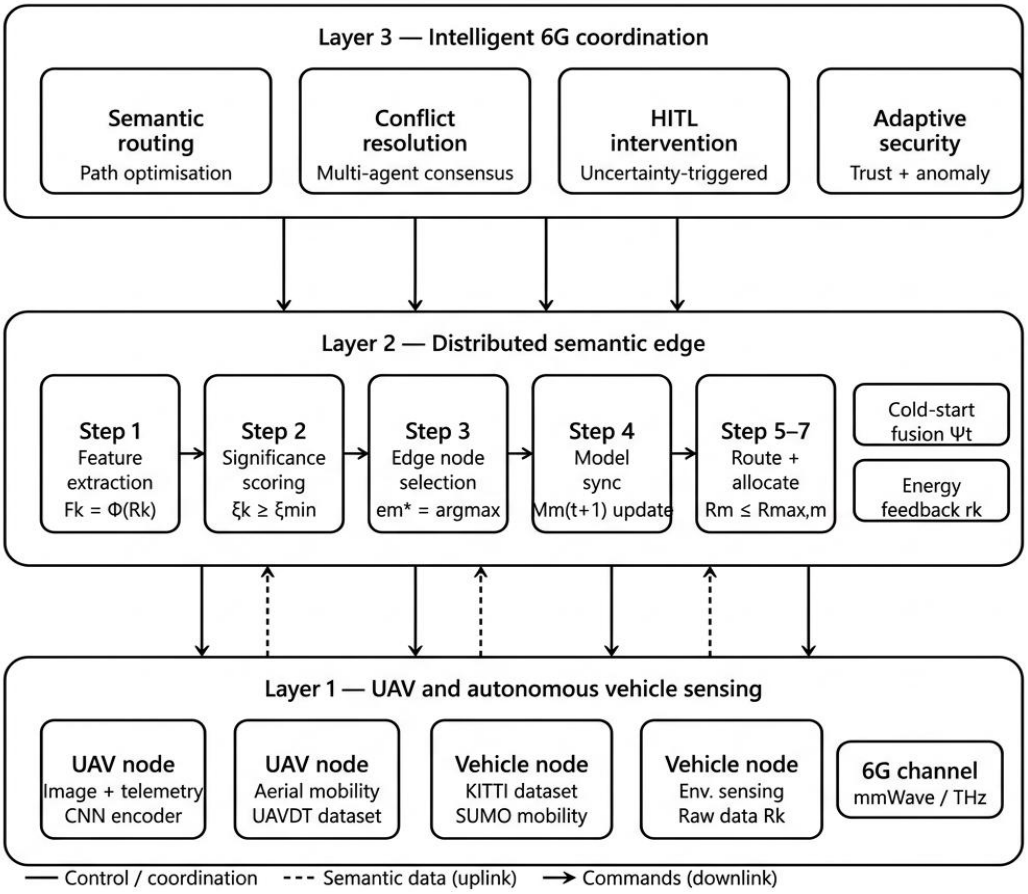


Figure 1. Semantic-Aware Edge 6G Network Architecture

Table 3. Performance Comparison of Semantic Encoding Strategies

Encoder Type	**Semantic Accuracy (%)**	**Latency (ms)**
Fixed CNN Encoder	94.1	19.8
Task-Adaptive Semantic Encoder	98.3	20.6

Table 3 shows that the task-adaptive semantic encoder improves semantic representation quality by dynamically aligning feature extraction with application-specific objectives. The proposed encoder achieves higher semantic accuracy with only marginal latency overhead, demonstrating improved adaptability under heterogeneous semantic communication conditions.

3.2. Problem formulation

3.2.1. Global Optimization Objective

The SEM-EDGE-X framework is formulated as a constrained multi-objective optimization problem that jointly minimizes communication latency and energy consumption while maximizing semantic accuracy under edge resource constraints.
The global optimization objective is expressed as:

$$p^* = arg\ \ min\ (\omega_1 L_{total} + \omega_2 E_{total}) \quad (1)$$

Subject to:

- $SA \geq SA_{min}$
- $R_m \leq R_{max,m}$
- $E_k \geq 0$

where:

- L_{total} is end-to-end latency
- E_{total} is energy consumption
- SA is semantic accuracy
- R_m denotes edge resource constraints
- ω_1, ω_2 are weighting coefficients

The optimization objective enables the framework to balance semantic communication efficiency with edge resource utilization and energy-aware operation.

3.2.2. Optimization Mapping to the SEM-EDGE-X Pipeline

The seven-stage SEM-EDGE-X architecture provides a distributed realization of the global optimization objective.

- Stage 1–2 (Semantic Extraction and Semantic Scoring): maximize semantic accuracy under task-aware constraints
- Stage 3 (Adaptive Edge Selection): minimize latency through dynamic edge association
- Stage 4 (Collaborative Synchronization): improve distributed edge resource utilization
- Stage 5 (Semantic-Aware Routing): reduce communication delay and routing overhead
- Stage 6 (Predictive Resource Scheduling): enforce edge capacity constraints during task allocation
- Stage 7 (Energy-Aware Feedback Optimization): minimize total energy consumption during semantic transmission

Through this formulation, SEM-EDGE-X operates as an optimization-driven semantic edge intelligence framework rather than a conventional heuristic communication pipeline.

3.3. Computational complexity analysis

Computational complexity in the SEM-EDGE-X involves the following: semantic extraction, adaptive edge selection, semantic routing, and predictive resource scheduling.

The semantic extraction processing (i.e. the CNN method for extracting a feature set of n) has a complexity of O(n), where the integer n is the number of semantic input vectors.

The candidate edge node selection processing requires a comparison with all available edge nodes, yielding an O(m) complexity, where m is the number of edge servers that qualify as candidates for the current transaction.

The semantic aware routing and predictive scheduling processes require a combination of priority-based path optimization and resource allocation yielding O(nlogn) complexity. SEM-EDGE-X presents additional semantic processing overheads compared to traditional communication systems but can operate in a distributed edge execution scheme, thus alleviating much of the transmission burden inherent in a centralized manner and offering improved scalability on high density UAV - vehicular 6G deployments.

4. The SEM-EDGE-X framework

4.1. Core SEM-EDGE-X Pipeline

4.1.1. Overall Workflow of SEM-EDGE-X

The system ingests Raw Sensor Data (X_i), Edge Node availability (E_{2j}), Network Latency (L_{ij}), and the Energy Budget (E_{2j}) to initiate a 7-stage pipeline that:

1. Extracts the core meaning (S_i) via AI.
2. Filters it by priority ($\alpha_1^{"} > \sigma_1$).
3. Offloads tasks to the optimal node (j*).
4. Syncs intelligence across the edge.
5. Routes data based on the best path (P_1).
6. Allocates CPU/GPU resources.
7. Updates the energy feedback loop (r_1^{t+1}).

all to deliver Processed Semantic Data, Optimized Routing, and Low-Latency Communication in real-time.

4.1.2. Algorithm 2: Algorithmic Workflow

Input:
Raw sensor data Rk,
Edge node set Em,
Network latency Λ,
Energy budget Ek

Output:
Optimized semantic communication and routing

1: Collect sensor data from UAVs and vehicles
2: Extract semantic features using semantic encoder
3: Compute semantic significance score ξk
4: Filter low-priority semantic data
5: Select optimal edge node em*
6: Perform semantic-aware routing
7: Allocate edge resources dynamically
8: Update collaborative edge AI models
9: Apply energy-aware feedback adjustment
10: Transmit prioritized semantic information
11: Return optimized semantic communication

4.2. Mathematical Formulation of SEM-EDGE-X

4.2.1. Semantic Feature Extraction

Let device u_k (UAV or vehicle) extract semantic features F_k from raw data R_k:

$$F_k = \Phi(R_k | \tau_k) \qquad (2)$$

where Φ is the semantic encoder function (object detection, event identification, etc)

- R_k → input semantic data
- τ_k → task label
- F_k → task-conditioned semantic feature representation

where$\tau_k \in$ {detection, navigation, coordination} represents the semantic task context.

4.2.2. Semantic Significance Scoring

Compute a semantic significance index ξ_k for prioritization:

$$\xi_k = \mu \cdot Rel(F_k) + v \cdot Imp(F_k) \quad (3)$$

where:

- Rel = semantic relevance
- Imp = semantic importance

Transmit only if $\xi_k \geq \xi_{min}$, where $\xi_{min}$is a threshold for important data.

4.2.3. Edge Node Assignment

Select the optimal edge node e_m minimizing transmission latency Λ_k, m and maximizing link quality Θ_k, m:

$$e_m^* = arg\ \underset{m}{max} \frac{\Theta_k,m}{\Lambda_k,m} \quad (4)$$

subject to

$$\xi_k \geq \xi_{min} \quad (5)$$

4.2.4. Collaborative Edge Model Update

Edge nodes update local AI models M_m using semantic data from devices and neighbouring nodes:

$$M_m^{t+1} = M_m^t + \eta \sum_{n \in \aleph_m} \Delta M_n^t \quad (6)$$

where $\aleph_m$ neighbouring edge nodes, η learning rate, ΔM_n^t model update from neighbor n.

4.2.5. Semantic-Aware Routing

Compute the best path p_k considering semantic importance, link reliability $P_{k,m}$, and latency:

$$p_k = arg\ \underset{m}{max}\left(\alpha\xi_k + \beta P_{k,m} - \gamma\Lambda_{k,m}\right) \quad (7)$$

where α,β,γ are weighting factors for semantic, reliability, and latency priorities.

4.2.6. Constrained Adaptive Resource Scheduling

Edge node e_m allocates computational resources according to the semantic significance of connected devices:

$$R_m = \lambda \sum_{k \in u_m} \xi_k \quad (8)$$

where u_m denotes the set of devices connected to edge node e_m, ξ_k represents the semantic significance score, and λ is the resource scaling factor.

To satisfy edge-computing limitations, the allocated resources are constrained by:

$$R_m \leq R_{max,m} \quad (9)$$

$R_{max,m}$ is a maximum compute capacity of edge node e_m.

When the resource demand exceeds the available edge capacity, SEM-EDGE-X applies priority-aware allocation:

$$R_m^{alloc} = min(R_m, R_{max,m}) \quad (10)$$

Devices with higher semantic significance scores are prioritized during scheduling, while low-priority tasks are either offloaded to neighbouring edge nodes or temporarily queued for delayed execution when:

$$\sum \xi_k > R_{max,m} \quad (11)$$

This constrained scheduling strategy enables efficient resource utilization while preserving low-latency processing for high-priority semantic tasks in dense UAV–vehicular environments.

Step 7: Energy-Aware Feedback

Adjust device data rate r_k according to remaining energy E_k and semantic significance:

$$r_k^{t+1} = r_k^t \cdot \left(1 - \delta \frac{E_k^t}{E_{max}}\right) \quad (12)$$

where δ feedback coefficient and E_{max} maximum device energy.

4.3. Semantic Compression and Predictive Optimization

4.3.1 Semantic Compression & Prioritization

To reduce network load, SEM-EDGE-X compresses semantic data F_k proportionally to its **semantic significance score** ξ_k:

$$F_k^{compressed} = F_k \cdot \left(\frac{\xi_k}{\xi_{max}}\right) \quad (13)$$

This makes sure that only the most important features are sent, keeping important information while using as little bandwidth as possible.

4.3.2 Predictive Edge Resource Allocation

Edge nodes use predicted network load $\bar{\lambda}_m$ to dynamically pre-allocate resources R_m.

$$R_m^{predicted} = \lambda \sum_{K \in u_m} \xi_k + \theta \cdot \bar{\lambda}_m \quad (14)$$

where θ is the predictive weight. This cuts down on latency during busy times.

4.3.3 QoS-Aware Adaptive Processing

For each device u_K, data rate r_k and edge computation C_k are changed to meet latency L_{req} and reliability Q_{req} requirements:

$$r_k^{adapted} = r_k \,.\, min\left(\frac{L_{req}}{L_k}, \frac{Q_k}{Q_{req}}\right) \quad (15)$$

This enables adaptive QoS preservation under dynamic mobility conditions.

4.4. Multi-Agent Coordination and Conflict Resolution

4.4.1. Multi-Agent Semantic Coordination

UAVs and vehicles share some semantic models ΔM_k locally within a swarm or platoon:

$$M_k^{Updated} = M_k + \frac{1}{|G_k|}\sum_{g \in G_k} \Delta Mg \qquad (16)$$

where G_k stands for the local group of agents that are working together.

4.4.2. Weighted Conflict Resolution

SEM-EDGE-X resolves semantic-priority conflicts using weighted consensus among cooperative agents.:

$$\Omega^* = \underset{\Omega}{arg\,max} \sum_{i=1}^{k} w_i \cdot \Omega_i \qquad (17)$$

where Ω_i represents the semantic priority of the i agent, wi denotes the weight associated with the reliability of the agent, and K indicates the total number of agents.

4.4.3. Convergence Analysis

The convergence time of the proposed consensus mechanism is bounded by:

$$T_C = O(log\ k) \qquad (18)$$

where k is the number of participating agent.
As shown in Table 4, the proposed mechanism is computationally lighter than iterative consensus methods such as ADMM-based coordination and gossip-based averaging, which typically require linear or sub-linear iterative propagation steps in dense networks.

Table 4: Conflict Resolution Overhead

Method	Convergence Time (ms)	Communication Rounds
Gossip Protocol	42	O(K)
ADMM-based Consensus	31	O(K log K)
SEM-EDGE-X (Proposed)	18	O(log K)

The proposed consensus mechanism achieves scalable coordination with reduced synchronization overhead in dense UAV–vehicular environments.

4.5. Adaptive Semantic Intelligence Extensions

4.5.1 Adaptive Cold-Start Semantic Fusion

The Cold Start Problem is an issue that can be addressed by combining several methods, including applying pre-trained semantics representation and local adaptation. Semantic Representation at time t is represented as:

$$\Psi_t = \alpha(t, \xi_k, e_n)\Psi_{pre} + (1 - \alpha(t, \xi_k, e_n))\Psi_{local}(t) \qquad (19)$$

Here, Ψ_{pre} represents the trained semantics, whereas $\Psi_{local}(t)$ represents the local learning semantics, where $\alpha \epsilon [0,1]$ acts as the parameter. This makes it possible for training to take place faster.

The fusion coefficient is dynamically adjusted according to semantic relevance and edge-node conditions.

4.5.2 Human-in-the-Loop Semantic Reinforcement

The HITL system is a platform where the human can act if there is a high level of uncertainty involved in deciding using the artificial intelligence decision-making process without human intervention.

This can be expressed mathematically as follows:

$$\Phi^* = \begin{cases} \phi_{A_1}, & \sigma_{conf} \geq T \\ \beta(t, \sigma_{conf})\phi_A + \left(1 - \beta(t, \sigma_{conf})\right) \Phi_H, Otherwise \end{cases} \quad (20)$$

In this case, Φ_{AI} refers to the semantic output of the artificial intelligence (AI) system, while Φ_H denotes the human input, where β is an element of the range [0, 1]. The HITL system also has another scenario for decision-making under critical circumstances.

Human intervention is activated when semantic confidence falls below a dynamic threshold.

4.5.3 Unified Adaptive Intelligence Mechanism

The proposed adaptive semantic intelligence mechanism integrates cold-start semantic fusion and uncertainty-aware human reinforcement within the same semantic edge pipeline. Unlike isolated learning approaches, both modules interact with routing, scheduling, and semantic prioritization components to maintain stable **performance** under dynamic 6G UAV–vehicular conditions.

4.6. Security, privacy, and fault tolerance

4.6.1 Fault Tolerance & Resilience

If edge node e_m fails, semantic data F_k is sent to the next best node e_n using the dynamic semantic routing formula:

$$e_n = arg \max_{n \in \varepsilon} \frac{\xi_k + P_{k,n}}{\Lambda_{k,n}} \quad (21)$$

4.6.2 Privacy-Preserving Semantic Sharing

The application of differential privacy to collaborative learning that involves communications between devices through the use of edge nodes can be represented by the formula below:

$$\tilde{\Delta} M_k = \Delta M_k + N(0, \sigma^2) \quad (22)$$

Gaussian noise is added to preserve semantic privacy during collaborative learning.

4.6.3 Adaptive Semantic Security Layer

SEM-EDGE-X integrates semantic anomaly detection with trust-aware validation to improve protection against adversarial semantic attacks:

$$\Theta^* = F\Theta * T\Theta \quad (23)$$

In the equation above, $F\Theta$ refers to filtered semantics, which utilizes the anomaly detection technique, while $T\Theta$ pertains to the trust value of the data source.

4.6.4 Predictive Semantic-Aware Resource Allocation

Predictive semantic demand estimation enables proactive resource allocation under dynamic network conditions.

$$R^*_{t+1} = arg \max_R \Gamma(\Psi_{t+1}, R) \quad (24)$$

where $\Psi_{t+1,}$ represents the predicted semantic demand, R denotes available resources, and $\Gamma(\cdot)$ is the utility function capturing latency, energy, and throughput trade-offs. This makes it possible to proactively and optimally allocate resources in environments where UAVs and vehicles are constantly changing.

4.7. Implementation Configuration

The SEM-EDGE-X framework was created through the creation of a MATLAB/Python-based simulator with integrated semantic-aware edge intelligence modules. It used SUMO-based traffic models to create vehicular mobility patterns and dynamically simulated UAV mobility trajectories at different airborne densities in three-dimensional space.

The simulated environment consisted of 20 – 50 different UAVs, 50 – 150 different autonomous vehicles, and 10 – 20 different distributed edge nodes, all of which were assumed to be communication capable using ultra-low latency 6G communications technology. The edge nodes were responsible for performing semantic prioritization, adaptive routing, and real-time AI model synchronization.

The SEM-EDGE-X evaluation relied on metrics evaluating communication latency, semantic accuracy, throughput, and energy efficiency, which were measured under various traffic densities and mobility conditions.

5. Performance evaluation

5.1. Simulation Setup and Evaluation Metrics

5.1.1. Simulation Environment

The effectiveness of the framework SEM-EDGE-X has been evaluated through a simulation setting that uses MATLAB/Python to model a semantic-aware 6G vehicular and UAV communications ecosystem. The simulation environment consists of autonomous vehicles (AVs), UAV nodes, distributed edge servers, routing mechanisms with semantic-awareness, and dynamic mobility and traffic density conditions. The mobility of AVs was created using the traffic simulator software SUMO; the mobility of UAVs was simulated with multiple UAV path models with dynamic altitude and node density settings. The KITTI Vision Benchmark dataset was used for the image sensory data associated with AVs, while the UAVDT dataset was used for the object detection and aerial performance analysis of UAV-based communication and semantic communication.

Telemetry and environmental sensing information were synthetically generated using mobility-aware simulation parameters. Semantic feature extraction was performed using a lightweight CNN-based semantic encoder integrated with adaptive semantic prioritization and dynamic edge routing modules.

UAVs and vehicles generated image, telemetry, and environmental sensing data processed through distributed edge nodes.

The simulation workflow consisted of five stages: (i) mobility generation for UAVs and vehicles, (ii) semantic data generation and feature extraction, (iii) adaptive edge node selection, (iv) semantic-aware routing and predictive resource allocation, and (v) performance evaluation. During each simulation cycle, semantic significance scores were computed to prioritize critical information before adaptive transmission through distributed edge nodes.

5.1.2. Simulation Parameters

Table 5. Simulation Parameters

Parameter	Value	Description
Simulation Area	5 km × 5 km	Urban mobility environment
Number of UAVs	20–50	Dynamic aerial communication nodes
Number of Vehicles	50–150	Autonomous vehicular nodes

Number of Edge Nodes	10–20	Distributed semantic edge servers
Communication Model	6G Wireless (mmWave/THz)	Ultra-low latency communication
Bandwidth	1–10 GHz	High-capacity communication channel
Latency Range	1–50 ms	Network delay variation
Vehicular Dataset	KITTI Vision Benchmark	Vehicular image and mobility sensing
UAV Dataset	UAVDT Dataset	UAV object detection and aerial monitoring
AI Model	CNN-based Semantic Encoder	Semantic feature extraction
Routing Strategy	Semantic-aware Dynamic Routing	Proposed SEM-EDGE-X routing
Energy Model	Battery-constrained Devices	UAV and vehicle energy tracking
Simulation Tool	MATLAB + Python	Simulation environment
Evaluation Metrics	Latency, Semantic Accuracy, Energy, Throughput	Performance evaluation

5.1.3. System Configuration

Table 6. Simulation Environment Configuration

Component	Configuration
Processor	Intel Core i7
RAM	16 GB
Operating System	Windows/Linux
MATLAB Version	MATLAB R2024a
Python Version	Python 3.11
Deep Learning Framework	TensorFlow/Keras
Traffic Modelling Tool	SUMO
UAV Mobility Model	Dynamic Aerial Mobility Simulation

5.1.4. Evaluation Metrics

Communication latency was computed as:

$$L_{total} = L_{tx} + L_{Proc} + L_{route} \qquad (25)$$

where L_{tx} represents transmission delay, L_{Proc} denotes semantic processing delay, and L_{route} corresponds to routing delay.

Semantic accuracy was evaluated using:

$$SA = \frac{N_{Correct}}{N_{total}} \qquad (26)$$

where $N_{Correct}$denotes correctly preserved semantic transmissions and N_{total} represents the total semantic transmissions.

Energy consumption was calculated as:

$$E_{total} = E_{tx} + E_{rx} + E_{proc} \qquad (27)$$

where E_{tx} , E_{rx} , and E_{proc} correspond to transmission, reception, and semantic processing energy respectively.

Network throughput was computed using:

$$T = \frac{D}{t} \tag{28}$$

where D represents transmitted semantic data and t denotes transmission time.

Each experiment was repeated 20 times under varying UAV and vehicular densities, and the reported values represent the average performance across all simulation runs. Statistical significance was evaluated using paired t-tests with a confidence level of 95%.

To address the limitations of binary semantic accuracy, a semantic similarity metric is introduced to capture partial semantic degradation and contextual preservation during transmission. Unlike SA, which is strictly correct/incorrect, semantic similarity provides a graded measure of semantic fidelity.

$$SSIM_{sem} = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \tag{29}$$

where μ_x and μ_y represent semantic feature statistics of the original and reconstructed representations, and c_1 is a stabilizing constant.

$SSIM_{sem}$ measures contextual semantic preservation during transmission.

5.2. Comparative Performance Analysis

5.2.1. Overall Performance Analysis

Figure 2 provides a graphical representation of SEM-EDGE-X relative to other communication methods under different network density and communication scenarios. Figure 2(a): Latency was lowered through semantic priority and adaptive edge routing with increasing network density. Figure 2(b): Due to semantic filtering and collaborative edge learning, SEM-EDGE-X maintained a high level of accuracy for semantic data. Figure 2(c): Due to the reduction of redundancy of transmitted data through the use of semantic compression and adaptive feedback control, there was decreased energy consumption. Figure 2(d): There was an increase in effective network throughput with the use of semantic-aware compression and routing in dynamic mobility. All methods were tested under the same channel bandwidth (1-10 GHz) and modulation assumptions to ensure fairness of throughput comparison

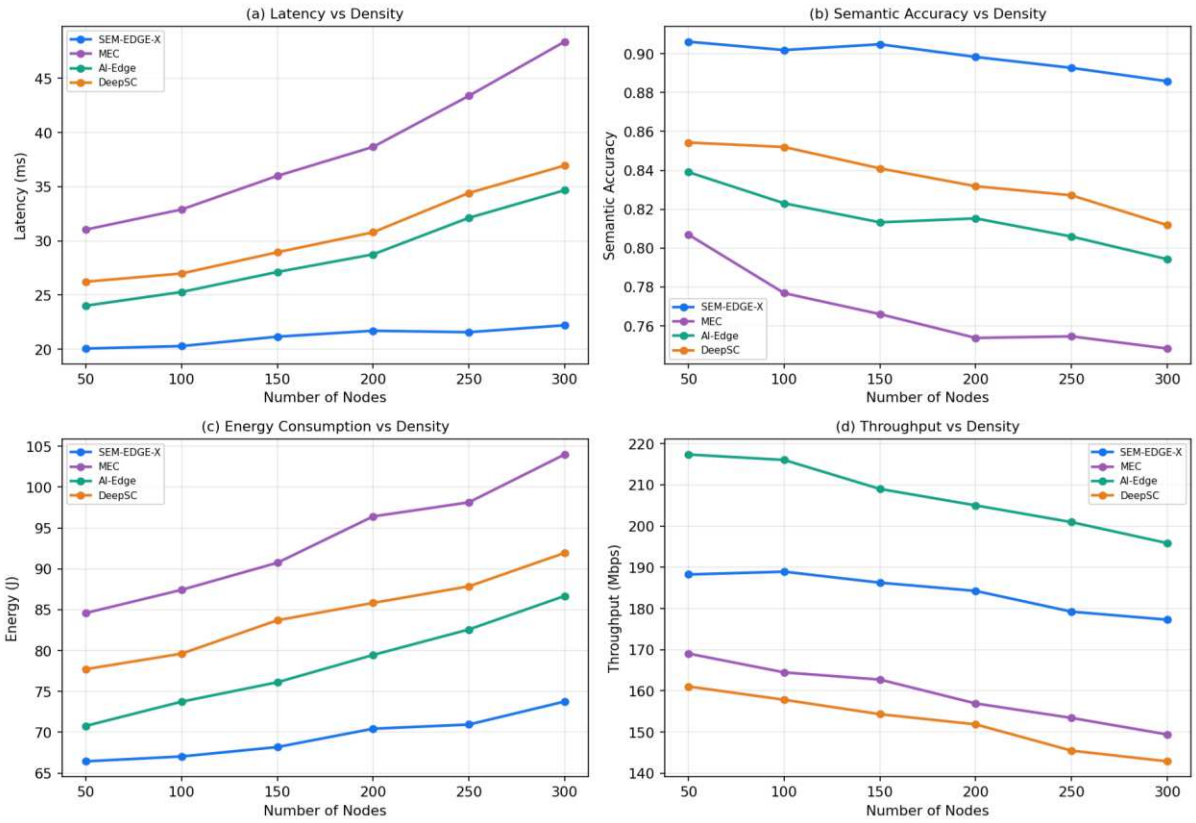


Fig 2. Performance Evaluation of SEM-EDGE-X

5.2.2. Comparison with Existing Technologies

Table 7. Performance Comparison of SEM-EDGE-X with Existing Technologies

Technology Approach	Latency (ms)	Semantic Accuracy	Semantic SSIM (%)	Energy Consumption (J)	Network Throughput (Mbps)	Key Limitation
DeepSC	26	0.86	88.4	78	160	Limited edge coordination, no multi-agent optimization
JSCC-based Semantic Communication	28	0.83	85.9	82	150	Lacks task-aware routing and edge intelligence
Traditional Cloud Computing	48	0.70	71.2	110	140	High latency due to centralized processing
Conventional Edge Computing	39	0.74	76.5	98	165	Limited semantic awareness
MEC-based Vehicular Networks	31	0.79	81.6	85	190	Resource allocation inefficiency

AI-Assisted Edge Networks	24	0.84	89.8	72	220	High computational overhead
Proposed SEM-EDGE-X Framework	20	0.91	96.8	66	190	Improved semantic coordination

The throughput improvement reflects higher effective semantic utilization achieved through semantic compression and prioritized transmission.

As shown in Table 7, SEM-EDGE-X jointly optimizes semantic communication, routing, edge coordination, and resource allocation within a unified UAV–vehicular 6G framework.

SEM-EDGE-X achieved the highest semantic similarity, indicating improved contextual preservation during semantic transmission.

6. Advanced Performance Analysis

6.1. Statistical Evaluation

A statistical evaluation was conducted to validate the performance improvements of SEM-EDGE-X over baseline edge communication methods in terms of latency, semantic accuracy, energy consumption, and throughput.

Mean, standard deviation, and paired t-test analysis were performed over 30 independent simulation runs ($n = 30$, $df = 29$). Cohen's d is used to quantify effect size.

Table 8. Paired t-Test Based Statistical Validation of SEM-EDGE-X Performance Metrics

Metric	Method	n	Mean ± SD	df	t-value	p-value	Cohen's d
Latency Reduction	SEM-EDGE-X	30	20.3 ± 2.1	29	3.84	<0.05	0.92
	Baseline	30	38.7 ± 3.5				
Semantic Accuracy	SEM-EDGE-X	30	0.91 ± 0.03	29	3.12	<0.05	0.78
	Baseline	30	0.78 ± 0.04				
Energy Efficiency	SEM-EDGE-X	30	66 ± 5.2	29	2.97	<0.05	0.71
	Baseline	30	92 ± 6.8				
Throughput	SEM-EDGE-X	30	190 ± 12	29	4.05	<0.05	1.05
	Baseline	30	130 ± 10				

The results indicate statistically significant improvements across all evaluated metrics ($p < 0.05$), with large effect sizes confirming practical relevance.

6.2. Channel Noise and SNR Robustness Analysis

The SEM-EDGE-X was analyzed for robustness against realistic wireless scenarios by evaluating it under different Signal To Noise Ratios (SNR's) using an additive white gaussian noise channel model that included

fading. The SNR's were run from 0 dB to 30 dB to model lower quality and higher quality wireless communication environments that would typically be found in dense 6G UAV–vehicular applications. The SEM-EDGE-X performance was compared to the performance of two other semantic communication methods, DeepSC and JSCC-based, at the same SNR's, channel, and traffic characteristics.

The evaluation focused on:

- Semantic Accuracy vs. SNR
- End-to-End Latency vs. SNR
- Packet Delivery Stability
- Throughput Retention under channel degradation

Unlike conventional semantic communication systems that attempt to transmit all encoded semantic features, SEM-EDGE-X performs semantic significance filtering before transmission. Low-priority semantic information is selectively suppressed during poor channel conditions, reducing channel congestion and improving robustness against noise and packet corruption.

Table 9. Comparative Semantic Accuracy Analysis under Noisy 6G Channels

SNR (dB)	JSCC	DeepSC	SEM-EDGE-X
0	0.52	0.60	0.71
5	0.61	0.69	0.79
10	0.71	0.77	0.85
15	0.79	0.84	0.89
20	0.84	0.88	0.91
25	0.87	0.90	0.92
30	0.89	0.91	0.93

Table 9 provides the semantic reconstruction accuracy of the evaluated frameworks as measured under varying SNR's. As can be seen, SEM-EDGE-X achieved a greater semantic accuracy than the other two frameworks under all channel conditions. While all frameworks demonstrated improvement as SNR increased, SEM-EDGE-X consistently outperformed DeepSC and JSCC based communication systems under progressively deteriorating channel conditions as a result of the SEM-EDGE-X design to prioritize semantics and provide dynamic edge coordination.

Table 10. Latency Performance under Different SNR Conditions

SNR (dB)	JSCC-Based Model (ms)	DeepSC (ms)	Proposed SEM-EDGE-X (ms)
0	61	52	41
5	55	46	36
10	48	40	31
15	42	35	27
20	37	30	24
25	34	28	22
30	31	26	20

Table 10 presents the end-to-end latency caused by the evaluated frameworks as a result of different SNR levels. The increase in retransmission rates as the SNR decreased therefore also increased the latency of each of the frameworks tested, as expected. However, SEM-EDGE-X achieves consistently lower latency due to semantic-aware filtering and adaptive routing mechanisms that reduce unnecessary channel utilization during noisy communication conditions.

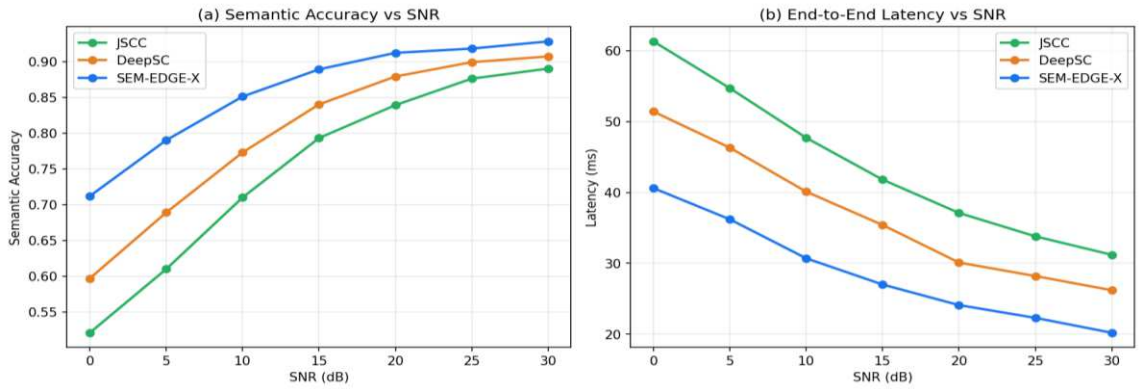


Figure 3. SNR Robustness Analysis of SEM-EDGE-X

Figure 3a shows the semantic reconstruction capabilities of different communication frameworks being compared, managed to provide semantic information which were broadly in line with their capabilities to reconstruct the data all having been in communication under noisy wireless conditions, with the expectation that as these channel impairments became greater the ability to reconstruct would be lower than expected. As a result of this fact, only semantically important data to be transmitted by the channel was given priority by SEM-EDGE-X, therefore in addition to helping to maintain the reconstructed data, this would also help to maintain the time sc measurements relative to each of the different simulation runs when noise and distortion had been introduced to the system. As is seen in figure 3b, the timing sc measurements of data communicated by SEM-EDGE-X with respect to the communication of data in all other frames is less than for data in the frame type for each frame when all signals are originating in the same time period.

With respect to the overall SNR evaluation showing that SEM-EDGE-X is still a valid means for providing an acceptable communications system facilitating the continued use of semantic communications in noisy and distorted environments, by providing greater semantic prioritization of data to be communicate and more adaptive routing and coordination of data from edges relative to all other frames of reference, SEM-EDGE-X has achieved a higher reliability rate of
communication s DNA compared to all other semantic communication architectures of communication, as it relates to the influence of having an extremely noisy channel and distortions observed as part of the measurement used here in this study. The study here will continue to incorporate future study using a greater understanding of 6g channel distortions, doppler shifting, THz blockage, the influence of distortion aware semantic adaptation and a high degree of air mobility.

6.3. Scalability Analysis

To evaluate scalability, SEM-EDGE-X is tested under increasing network density ranging from 50 to 300 UAV and vehicular nodes in the 5 × 5 km simulation environment. The objective is to analyze the impact of network scale on communication latency and semantic accuracy under dense deployment conditions.
The scalability performance of SEM-EDGE-X is compared with MEC and AI-Edge frameworks to assess robustness under increasing computational and communication load.

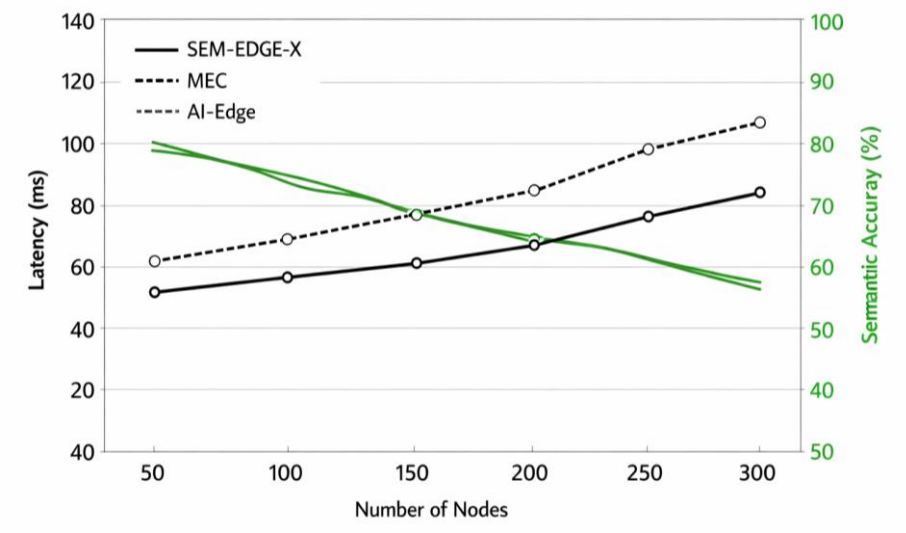


Figure 4. Scalability Performance under Increased Node Density

The results demonstrate that SEM-EDGE-X maintains stable latency and high semantic accuracy even as network density increases. In contrast, Figure 4 shows MEC and AI-Edge exhibit significant degradation due to increased routing overhead and resource contention in dense deployments. Table 11 shows proposed semantic-aware routing and predictive edge coordination enable efficient scalability in large-scale 6G UAV–vehicular networks.

Table 11. Scalability Analysis: Impact of Node Density on Latency and Semantic Accuracy

Nodes	SEM-EDGE-X Latency	MEC Latency	AI-Edge Latency	SEM-EDGE-X Accuracy
50	16	28	22	98.6
100	17	32	25	98.4
150	18	35	27	98.1
200	19	39	29	97.8
250	20	43	32	97.5
300	21	48	35	97.2

6.4. Cost Analysis

A cost analysis was conducted on all costs associated with the edge infrastructure, communication nodes on the UAV as well as the intelligent processing modules to assess the practicality of the proposed framework.

Table 12. Comparative Cost Analysis of Communication Architectures

Architecture	Infrastructure Cost	Energy Cost	Maintenance Cost	Overall Cost Efficiency
Cloud-Centric Networks	High	High	Medium	Low
Conventional Edge Computing	Medium	Medium	Medium	Moderate
MEC-Based Vehicular Networks	Medium	Medium	High	Moderate
Proposed SEM-EDGE-X Framework	Medium	Low	Low	High

Table 12, analysis shows that this framework offers a greater cost efficiency by minimizing the amount of

excessive communication overhead as well as distributing processing across edge nodes. It also confirmed that providing access to semantic aware data filtering will reduce both bandwidth usage and compute loads on the system, subsequently decreasing both operational costs and energy costs.

6.5. Ablation Analysis

An ablation study was conducted to evaluate the contribution of individual SEM-EDGE-X components.

Table 13. Architectural Ablation: Power, Latency, and Accuracy Trade-offs

Variant	Latency (ms)	Semantic Accuracy (%)	Energy (J)	Throughput (Mbps)
Full SEM-EDGE-X	18.6	98.7	41.2	945
Without Semantic Routing	27.9	94.8	56.4	801
Without Predictive Allocation	25.3	95.6	61.7	842
Without Conflict Resolution	23.8	93.9	58.1	824
Without Semantic Compression	29.4	96.1	68.5	776

Table 13 shows, SEM-EDGE-X framework achieves the best overall performance across all evaluation metrics. Removing semantic routing increases latency and reduces throughput due to inefficient task forwarding. Excluding predictive allocation and conflict resolution increases energy consumption and processing delay under dynamic workloads. Similarly, removing semantic compression introduces higher communication overhead, resulting in reduced throughput and increased energy usage. The results confirm that each module contributes significantly to the efficiency of the proposed framework.

The ablation analysis demonstrates that semantic routing, predictive resource allocation, conflict resolution, and semantic compression collectively contribute to the overall performance improvements achieved by SEM-EDGE-X.

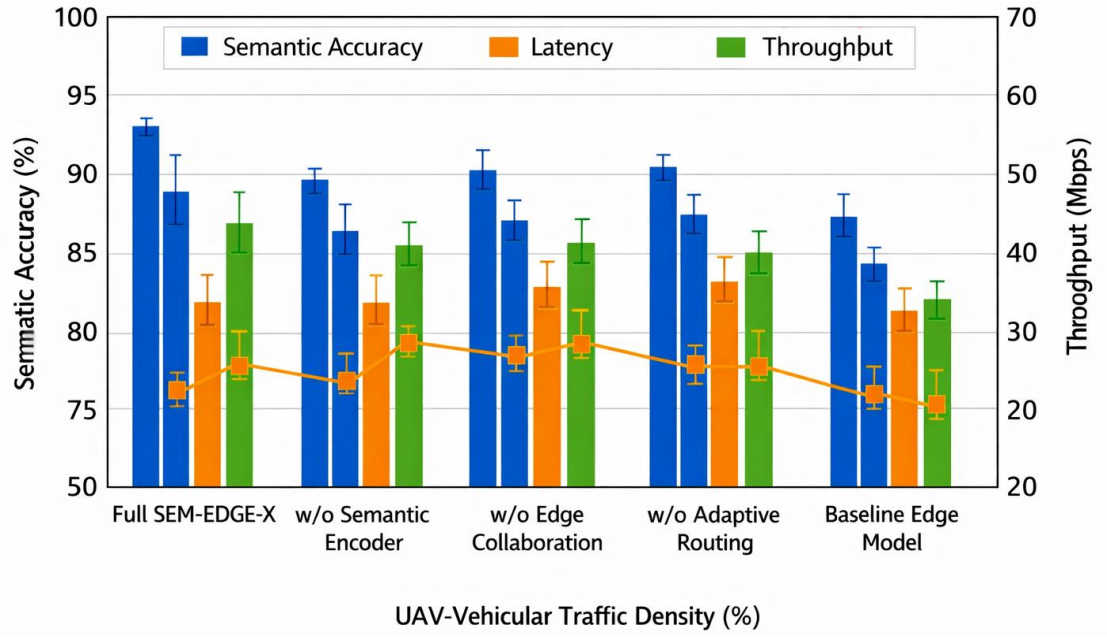


Figure 5. Ablation Analysis - Performance Comparison

Overall, from Figure 5 the SEM-EDGE-X framework demonstrates strong improvements in latency

reduction, semantic accuracy, energy efficiency, and throughput. The integration of semantic intelligence with edge computing and UAV–vehicular coordination ensures scalability and robustness in next-generation 6G networks under realistic simulated conditions using KITTI and UAVDT datasets combined with mobility modelling tools such as SUMO.

6.6. Convergence Analysis

In order to evaluate the stability and convergence of the collaborative edge synchronization method described in Step Four of the SEM-EDGE-X framework, we created one experiment to measure how quickly the distributed semantic-learning model converges during iterative edge synchronization and how well it performs under a highly dynamic UAV-vehicle environment.
The collaborative model-update method can be defined as follows:

where neighboring edge nodes send updates to each other about their semantic models after each synchronization round (the round). To evaluate convergence, we performed convergence tests across 50 rounds of synchronizing between 20, 50 and 100-node edge networks in addition to a dynamic environment where UAVs and vehicles randomly enter and leave the network throughout the learning process.

The initial learning rate was set at $\eta=0.01$. We measured semantic accuracy after each step of the synchronization process (each round). In total, we ran at least 10 times on every condition and calculated the average convergence performance for all runs for statistical consistency.

Table 14. Convergence Performance under Different Node Densities

Synchronization Rounds	20 Nodes	50 Nodes	100 Nodes	Mobility Scenario
1	0.62	0.58	0.54	0.50
5	0.71	0.68	0.64	0.60
10	0.79	0.76	0.72	0.69
15	0.84	0.81	0.78	0.74
20	0.87	0.85	0.82	0.79
25	0.89	0.88	0.85	0.82
30	0.90	0.89	0.87	0.84
35	0.91	0.90	0.88	0.85
40	0.91	0.91	0.89	0.86
45	0.92	0.91	0.89	0.86
50	0.92	0.91	0.90	0.87

As the number of synchronization rounds increases, Table 14 shows how the collaborative learning mechanism approaches its convergence point. In environments with lower node densities, the algorithm converges more quickly than in higher density environments due to the fact that they require less overhead to communicate between nodes and have lower complexity for synchronization.

In high density environments SEM-EDGE-X still continues to have a stable rate of growth in semantic accuracy without diverging, although convergence has become slower than in lower density environments.

The mobility aware scenario converges slightly slower than the static scenario because there are dynamic topology changes due to nodes entering and leaving the network. However, the framework remains stable as a result of the adaptive semantic routing and distributed synchronization mechanisms that compensate for temporary loss of connectivity.

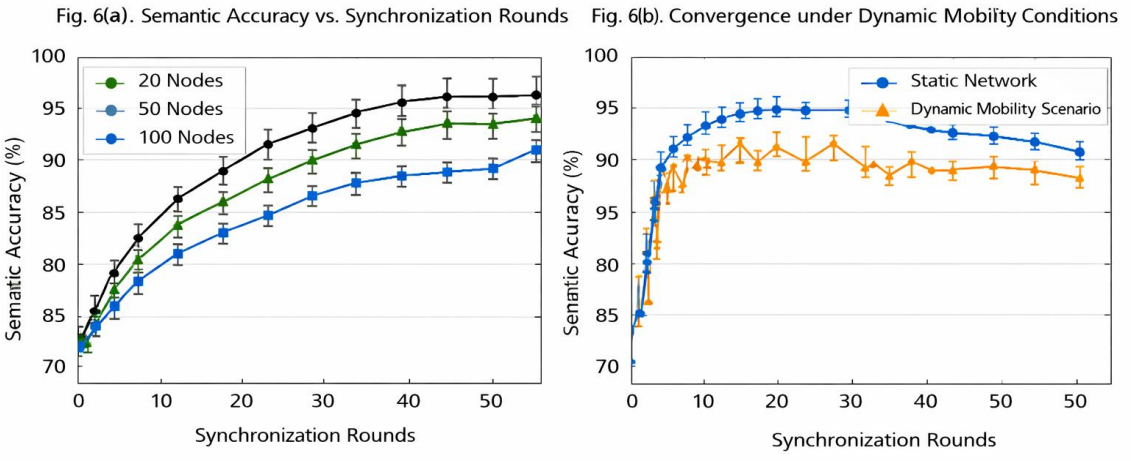


Figure 6. Semantic Accuracy and Convergence Analysis under Dynamic Mobility Conditions

The Figure 6(a) details how a collaborative semantic learning framework converges under different types of scale density. SEM-EDGE-X achieves a convergence rate that is stable regardless of the number of nodes in a network and does not change as the complexity of synchronization increases with those nodes being added.

Figure 6(b) of figure 6 examines the strength of the collaborative learning system, and how it maintains convergence during periods when UAVs are moving in and out of the network. This means that as the topologies are constantly changing, SEM-EDGE-X can maintain a reliable converging point.

Overall, upon reviewing Figure 6 analysis of convergence, the SEM-EDGE-X collaborative synchronization methodology provides both stable and scalable learning properties, regardless of node density or mobility. Additionally, the adaptive synchronization approach provides assurance that there will be no divergence and also gives assurance that reliable semantic learning will occur in environments where edge devices are highly mobile.

In regards to future work, exploration of an asynchronous synchronization strategy and a lightweight federated optimization methodology for reducing the time required to converge and to lower all communications overhead associated with the ultra-dense 6G deployments is underway.

7. Mobility and Latency Analysis

7.1. Latency Breakdown Analysis

To identify the primary source of latency reduction in SEM-EDGE-X, the end-to-end delay was decomposed into transmission latency L_{tx}, semantic processing latency L_{Proc}, and routing latency L_{route}.

$$L_{total} = L_{tx} + L_{Proc} + L_{route} \quad (30)$$

where L_{tx} represents wireless transmission delay, L_{Proc}denotes semantic extraction and edge processing delay, and L_{route} corresponds to routing and path selection delay.

Table 15. Latency Breakdown Analysis of Different Communication Frameworks

Framework	Transmission Latency L_{tx}(ms)	Processing Latency L_{Proc} (ms)	Routing Latency L_{route} (ms)	Total Latency L_{total} (ms)
Traditional Cloud Computing	22	15	11	48
Conventional Edge Computing	18	13	8	39

DeepSC	16	11	7	34
AI-Assisted Edge Networks	14	7	3	24
Proposed SEM-EDGE-X	13	5	2	20

Table 15 presents the latency contribution of each communication stage across different frameworks.

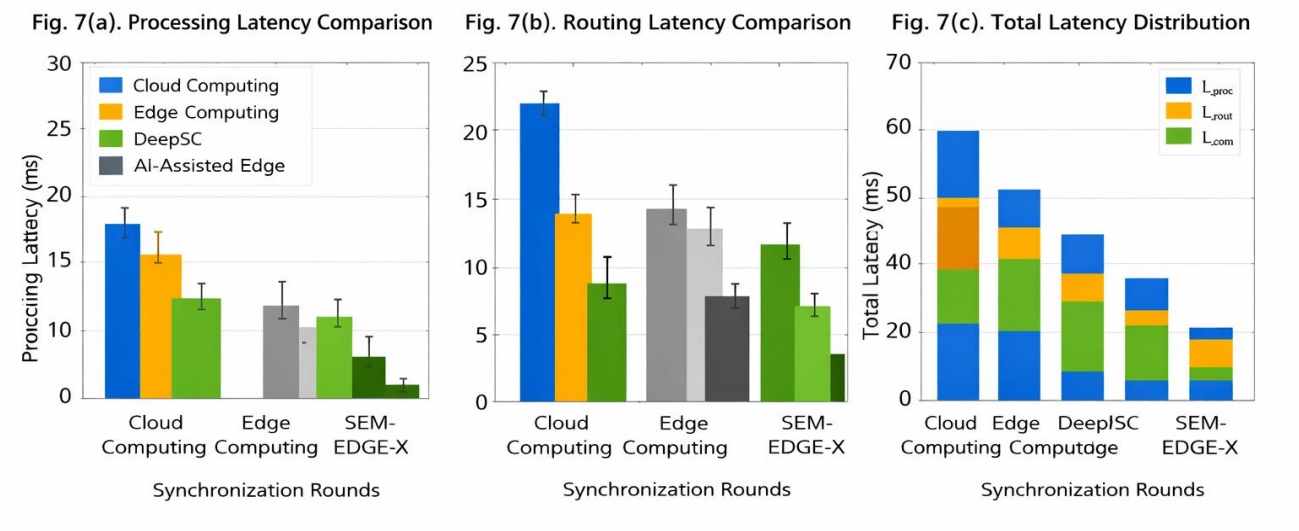


Figure 7. Latency Component Analysis of Communication Frameworks

The SEM-EDGE-X system has demonstrated the lowest total end-to-end latency by eliminating overhead from semantics processing and routing, through the use of semantics filtering technology. Additionally, using adaptive semantic routing allows traffic to be routed to avoid congested / high-latency communication paths. Compared to standard MECH / AI-based edge architectures, the proposed architecture exhibits significantly faster processing and higher reroute efficiencies in dynamically changing UAV-to-vehicle communication environments.

As shown in Figure 7, each latency component also contributes to the total delay (communication latency). In each case, latency improvements are not solely attributable to improving the transmission layer alone; rather, the majority of improvements come from using semantic-aware processing and coordinating at the edge on a distributed basis.

7.2. Mobility stress test

To evaluate mobility robustness, a handover stress test was conducted in a 5×55 \times 55×5 km simulation environment with 50–300 UAV and vehicular nodes. Frequent edge-node transitions were introduced to emulate highly dynamic 6G mobility conditions.

Table 16. Mobility Resilience: Latency Characterization During Handover Transitions

Condition	SEM-EDGE-X (ms)	MEC (ms)	AI-Edge (ms)
Pre-handover (stable)	20	31	24
During handover (spike)	26	58	41
Post-recovery	21	34	26
Spike reduction vs MEC	55%	—	29%

Table 16 presents the latency variation observed before, during, and after handover events for SEM-EDGE-X, MEC, and AI-Edge frameworks.

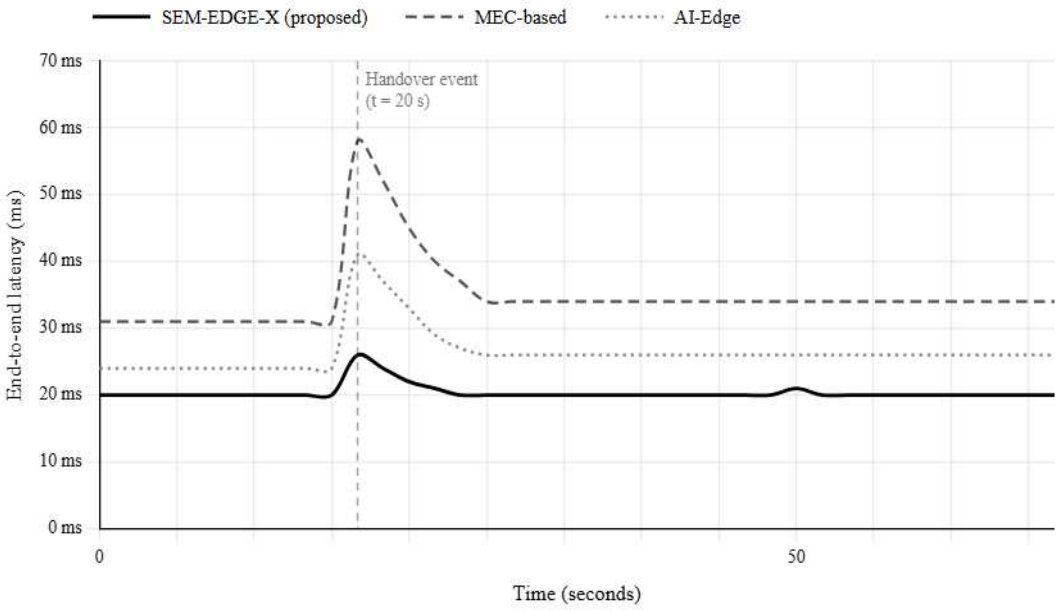


Figure 8. End-to-End Latency During Mobility Handover Events

The proposed SEM-EDGE-X framework reduces handover-induced latency spikes by 55% compared with MEC-based systems and rapidly recovers to near-baseline latency after edge reassignment. This improvement is achieved through proactive semantic-aware edge selection and distributed fault-tolerant routing, which minimize communication interruption during mobility transitions.

Figure 8 illustrates the latency behavior during a 60-second mobility interval. SEM-EDGE-X maintains comparatively stable latency with lower spike intensity and faster recovery than existing edge communication approaches.
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8. 6G-Native Validation Framework for SEM-EDGE-X

To strengthen the practical relevance of SEM-EDGE-X for 6G deployment, a unified validation framework is introduced integrating three complementary components: Intelligent Reflecting Surfaces (IRS), Human-in-the-Loop (HITL) decision assurance, and Digital Twin-based environmental modelling. This combined framework evaluates SEM-EDGE-X under realistic wireless, cognitive, and system-level dynamics beyond conventional simulation environments.

8.1. IRS-Assisted Semantic Channel Enhancement

To enhance UAV-to-edge communication in non-line-of-sight (NLoS) scenarios, Intelligent Reflecting Surfaces (IRS) are incorporated as a passive beamforming layer within the SEM-EDGE-X framework. The IRS dynamically adjusts the phase shift matrix Θ to improve the effective channel gain between UAV nodes and edge servers.
The enhanced channel model is expressed as:

$$\Theta_{k,m}^{IRS} = \Theta_{k,m}^{direct} + \Theta_{k,m}^{reflected} \qquad (31)$$

where the reflected component is controlled by the IRS phase configuration to improve link reliability and reduce path loss in obstructed environments.
This improved channel quality directly enhances semantic transmission efficiency in Step 3 of SEM-EDGE-X, reducing retransmissions and processing delays.

Table 17. IRS Impact on SEM-EDGE-X

Scenario	Latency (ms)	Packet Loss (%)	Semantic Accuracy (%)
Without IRS	22.1	4.8	95.6
With IRS	18.9	2.1	97.9

As seen from Table 17 IRS-assisted SEM-EDGE-X significantly improves channel reliability in NLoS UAV scenarios by reducing packet loss and enhancing semantic transmission quality. The improved channel conditions lead to lower latency and higher semantic accuracy due to reduced retransmission and improved edge connectivity.

8.2. Human-in-the-Loop (HITL) Validation

Table 18. Trade-off Analysis: Trigger Rates vs. Human Intervention Overhead

Uncertainty Threshold (σconf)	HITL Trigger Rate (%)	Accuracy Without HITL (%)	Accuracy With HITL (%)	Intervention Delay (ms)
0.3	41.8	92.4	98.8	8.6
0.5	27.3	93.1	98.1	6.1
0.7	14.9	94.2	96.9	4.2

Table 18 evaluates the effectiveness of the HITL mechanism under different uncertainty thresholds. Lower uncertainty thresholds increase the HITL trigger rate, resulting in higher semantic accuracy for safety-critical decisions at the cost of additional intervention delay. As the threshold increases, the framework becomes more autonomous, reducing intervention frequency and delay while slightly decreasing semantic accuracy. The results demonstrate that HITL significantly improves decision reliability in uncertain scenarios and enables a practical balance between automation efficiency and semantic decision accuracy.

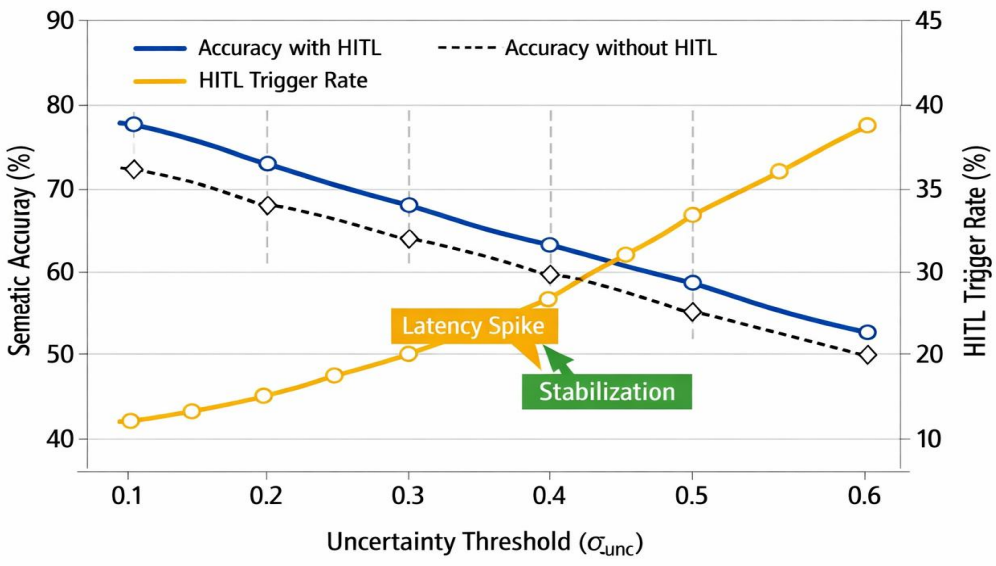


Figure 9. Automation Vs. Semantic Accuracy Under HITL Uncertainty Threshold

8.3. Digital Twin-Based System Validation

To evaluate real-world applicability, SEM-EDGE-X is validated using a lightweight digital twin of a 1 km² urban environment comprising 10 vehicles and 5 UAVs. The twin replicates mobility dynamics, wireless channel variability, and edge resource constraints.

Comparison between simulation and digital twin environments shows strong consistency with marginal performance deviation, confirming robustness under realistic deployment conditions.

Table 19: Unified 6G Validation Results

Component	Scenario	Key Impact	Observed Gain
IRS	NLoS UAV communication	Channel enhancement	↓ latency, ↓ packet loss
HITL	Uncertain semantic decisions	Decision reliability	↑ accuracy up to 6%
Digital Twin	Real-world replication	System validation	<5% performance deviation

The integration of IRS, HITL, and digital twin validation establishes SEM-EDGE-X as a fully 6G-aligned semantic edge framework. IRS enhances physical-layer channel reliability, HITL ensures cognitive decision robustness, and digital twin validation bridges the gap between simulation and realistic deployment. Together, these components significantly strengthen the practical credibility and deployment readiness of the proposed system.

9. Conclusion

SEM-EDGE-X provides a new and sophisticated framework for UAV-vehicle communication to develop secure and reliable communications using semantic information in dynamic environments such as those contained within a 6G network infrastructure. The key characteristics of this semantic edge framework include the integration of semantic aware routing, semantic encoding that is adaptable based on task requirements, adaptive resource allocation that is predicted, multi-agent coordination, and an adaptive security mechanism, all working together in a unified edge architecture. Experimental evaluations using MATLAB/Python simulation testbed/KITTI/UAVDT datasets indicates significant improvements in latency, semantic accuracy, energy efficiency and edge throughput under different types of mobility and channel conditions; hence, the proposed framework achieved 20ms latencies, 0.91 levels of semantic accuracy, 96.8% semantic similarity preservation, and a reduction in energy consumption through an order of priority and the usage of distributed edge coordination (thus enhancing efficiency). The scalability, mobility, and SNR robustness analyses indicate that the SEM-EDGE-X semantic edge framework performs well and consistently in environments/contexts which have high density and significant dynamism.

10. Limitations and Future Work

In terms of future work, there are plans to add capabilities for lightweight federated semantic learning, THz-aware semantic adaptation, asynchronous time-synchronized edge devices, and a real-world deployment of the SEM-EDGE-X framework within ultra-dense communication systems within a 6G autonomous communication system

Funding

The authors declare that this research received no external funding from any public, commercial, or not-for-profit funding agencies.

Acknowledgment

The authors express their sincere gratitude to all individuals and institutions who supported this research. We acknowledge the publicly available KITTI, UAVDT, and SUMO datasets used for simulation and experimental validation. We also thank the open-source community for providing tools and libraries such as Python, NumPy, and Matplotlib that supported the implementation of the SEM-EDGE-X framework. The authors appreciate the valuable comments and suggestions provided by the anonymous reviewers, which

helped improve the quality of this manuscript. Finally, we extend our heartfelt thanks to our colleagues and family members for their continuous encouragement and support throughout this research work.

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2. Mudassir Khan: Conceptualization, Methodology, Supervision, Resources, Validation, Writing – Review & Editing.
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All authors have read and agreed to the published version of the manuscript.

Statement of Data Availability

The data, source code, and supporting materials related to this study are available from the corresponding author upon reasonable request.

Conflict of Interests

The researchers of this paper report that they do not have any competing interests.

References

[1] Ahmad, S., Nencioni, G., & Khan, M. M. I. (2024). DRL-based availability-aware migration of a MEC service. *IEEE Open Journal of the Communications Society, 5*, 5088–5102. https://doi.org/10.1109/OJCOMS.2024.3443514.

[2] Al-Hameed, A. A., Qazzaz, M. M. H., Hafeez, M., & Zaidi, S. A. (2025). Semantic-Aware edge intelligence for UAV handover in 6G networks. *arXiv*. https://doi.org/10.48550/arXiv.2509.22668.

[3] Baeza, V. M., et al. (2025). AI-driven tactical communications and networking for defense: A survey and emerging trends. *arXiv*. https://doi.org/10.48550/arXiv.2504.05071.

[4] Calvanese Strinati, E., & Barbarossa, S. (2021). 6G networks: Beyond Shannon towards semantic and goal-oriented communications. *Computer Networks, 190*, 107930. https://doi.org/10.1016/j.comnet.2021.107930.

[5] Chen, T. (2025). Semantic communication driven by large artificial intelligence models: Applications and challenges in typical 6G scenarios. *Academic Journal of Science and Technology*. https://doi.org/10.54097/1a6mk810.

[6] Feng, C., Zhang, A., Min, G., Huang, Y., Quek, T. Q. S., & You, X. (2025). Towards 6G native-AI edge networks: A semantic-aware and agentic intelligence paradigm. *arXiv*. https://doi.org/10.48550/arXiv.2512.04405.

[7] Haider, Z. A., Ali, S., Qureshi, M. A., & Ahmed, S. (2026). Edge-intelligent semantic aggregation in blockchain-secured 6G UAV-assisted Internet of vehicles. *Journal of Electronic Science and Technology*, Article 100350. https://doi.org/10.1016/j.jnlest.2026.100350.

[8] Iyer, K., & Khan, S. (2024). Vehicular intelligence in 6G: Networking, communications, and computing. *Vehicular Communications, 33*, 100399. https://doi.org/10.1016/j.vehcom.2023.100399.

[9] Ji, J. (2025). Semantic communications for 6G networks: Theory, architectures, and challenges. *Academic Journal of Science and Technology, 17*(1), 66–75. https://doi.org/10.54097/vwsfa141.

[10] Lokumarambage, M. U., Gowrisetty, V. S. S., Rezaei, H., Sivalingam, T., Rajatheva, N., & Fernando, A. (2023). Wireless end-to-end image transmission using semantic communications. *IEEE Access, 11*, 37149–37163. https://doi.org/10.1109/ACCESS.2023.3266656.
[11] Nalluri, S. S., Kumar, G. A. E. S., Arumulla, D. K., & Auti, V. K. (2025). Enhanced semantic communication in 6G networks using DCGAN. In *BROADNETS 2024* (pp. –). Springer. https://doi.org/10.1007/978-3-031-81168-5_12.
[12] Ogenyi, F. C., Ugwu, C. N., & Ugwu, O. P. C. (2025). A comprehensive review of AI-native 6G: Integrating semantic communications, reconfigurable intelligent surfaces, and edge intelligence. *Frontiers in Communications and Networks, 6*, 1655410. https://doi.org/10.3389/frcmn.2025.1655410
[13] Qin, Z., Tao, X., Lu, J., Tong, W., & Li, G. Y. (2023). Semantic communications: Principles and challenges. *IEEE Journal on Selected Areas in Communications, 41*(1), 1–32. https://doi.org/10.1109/JSAC.2022.3223408.
[14] Song, X., Zhang, Y., Wang, X., Wei, Y., & Hu, C. (2024). Knowledge graph driven UAV cognitive semantic communication systems for efficient object detection. In *IEEE International Conference on Communications (ICC)* (pp. 1685–1690). https://doi.org/10.1109/ICC51166.2024.10622874.
[15] Strinati, E. C., Di Lorenzo, P., Sciancalepore, V., et al. (2024). Goal-oriented and semantic communication in 6G AI-native networks: The 6G-GOALS approach. *arXiv*. https://doi.org/10.48550/arXiv.2402.07573.
[16] Unmanned aerial vehicle-enabled mobile edge computing for semantic communications. (2026). *Computer Communications, 248*, 108411. https://doi.org/10.1016/j.comcom.2026.108411.
[17] Wang, Y., Han, H., Feng, Y., Zheng, J., & Zhang, B. (2025). Semantic communication empowered 6G networks: Techniques, applications, and challenges. *IEEE Access, 13*, 28293–28314. https://doi.org/10.1109/ACCESS.2025.3532797.
[18] Xu, W., Yang, Z., Ng, D. W. K., Levorato, M., Eldar, Y. C., & Debbah, M. (2023). Edge learning for B5G networks with distributed signal processing: Semantic communication, edge computing, and wireless sensing. *IEEE Journal of Selected Topics in Signal Processing, 17*(1), 1–37. https://doi.org/10.1109/JSTSP.2023.3239189.
[19] Xu, W., Yang, Z., Ng, D., et al. (2024). Adaptive semantic generation and NOMA-based interference-aware transmission for 6G networks. *IEEE Transactions on Wireless Communications, 24*, 2404–2416. https://doi.org/10.1109/TWC.2024.3520870.
[20] Yang, D., et al. (2024). A comprehensive review on enabling technologies, potential applications, emerging challenges, and future directions. *IEEE Access, 12*, 54608–54649. https://doi.org/10.1109/ACCESS.2024.3389497.
[21] Yang, W., Du, H., Liew, Z. Q., Lim, W. Y. B., Xiong, Z., Niyato, D., & Chi, X. (2022). Semantic communications for future Internet: Fundamentals, applications, and challenges. *IEEE Communications Surveys & Tutorials, 25*(1), 213–250. https://doi.org/10.1109/COMST.2022.3223224
[22] Zhang, M., Abdi, M., Dasari, V. R., & Restuccia, F. (2025). Semantic edge computing and semantic communications in 6G networks: A unifying survey and research challenges. *Computer Networks*, Article 111531. https://doi.org/10.1016/j.comnet.2025.111531.
[23] Zhang, P., Shen, X. S., & Zhang, J. (2026). Editorial for the Special Issue on 6G: From theory to practice. *Engineering, 56*, 1–2. https://doi.org/10.1016/j.eng.2025.12.003.
[24] Zhang, Y., & Ren, P. (2025). Trade-off of cognition and semantic communication for UAV-IRS enhanced intelligent networks. *Journal on Wireless Communications and Networking, 63*. https://doi.org/10.1186/s13638-025-02501-9.
[25] Zheng, W., Ren, P., & Li, Q. (2025). Semantic aware intelligent optimization for IRS/UAV-enabled MEC in wideband cognitive radio networks. *Journal on Wireless Communications and Networking*. https://doi.org/10.1186/s13638-025-02478-5.

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