A Context-Aware Semantic Resource Allocation Framework for Integrated Sensing and Communication in Vehicular Networks

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***Abstract*—The intersection of the Integrated Sensing and Communication (ISAC) and semantic communication is an opportunity for change in the next generation of vehicular networks. Nonetheless, current strategies do not have the capability of dynamically optimizing the resource allocation by collectively addressing dynamic wireless channel conditions, differentiating heterogeneous data semantics, and dynamic vehicular conditions. Thus, this paper suggests a new framework, Context-Aware Semantic Resource Allocation (CASRA), that posits resource allocation in the context of a multi-objective optimization problem, which seeks to maximize contextual semantic utility by realistically looking at physical constraints. The framework presents a dynamic weighting system, which calculates the semantic importance, depending on the criticality of messages, vehicle condition, and network properties. The full simulation in realistic conditions of 3GPP vehicular scenarios proves CASRA yields a semantic fidelity of 0.897, an increase of 66.7% over the Channel-Aware allocation, 41.4% over SA-VA-ISAC, and 76.5% over NOMA-based Semi-ISAC. Moreover, it minimizes the emergency communication latency by 35.8% over Channel-Aware allocation with a mean latency of 12.14 ms, and it achieves resource efficiency of 31.8% over the next-best approach. Under congested, emergency, and highway conditions, CASRA is highly performing and efficient and equitable at the same time. These findings suggest that CASRA offers a promising approach toward reliable, efficient, and intelligent 6G vehicular ecosystems.**

***Index Terms*—Integrated Sensing and Communication (ISAC), semantic communication, vehicular networks, resource allocation, context-aware systems, 6G networks.**

I. Introduction

THE evolution of intelligent transport systems (ITS) and autonomous vehicles poses challenges for next-generation vehicular networks as never before. These networks have to be able to ensure simultaneously ultra-reliable low-latency communication (URLLC), as well as high-precision environmental sensing, which is a convergence of physical and digital worlds [1], [2]. The requirements of vehicular safety applications are reflected by the stringent latency and reliability requirements which conform to the URLLC performance targets that are established under 5G and beyond [3]. This twofold need makes the Internet of Vehicles (IoV) a vital 6G application, in which vehicles create a data-heavy system of connections that produces a variety of heterogeneous data, including safety beacons and advanced sensor streams [4]. Traditional communication paradigms rely on bit-level reliability regardless of meaning or urgency. This is no longer sufficient for the diverse quality-of-service needs of IoV applications, especially under high mobility and density [1].

Integrated Sensing and Communication (ISAC) has become a core 6G technology, which combines sensing and communication in common hardware and waveforms to enhance spectral and hardware efficiency [5]. Nevertheless, the conventional ISAC resource allocation algorithms concentrate on the physical-layer optimization criteria such as radar estimation resolution and Shannon capacity, but do not account for semantic importance and application-level sensitivity of data streams [6], [7]. This restriction may cause the critical safety messages to be equally allocated resources to non-critical data when the channel conditions are similar.

Semantic communication exemplifies a paradigm shift from bit-centric to meaning-centric transmission. It substantially reduces bandwidth costs by conveying task-relevant information instead of raw sensor data [8], [9]. Semantically aware resource allocation methods employ methods of deep reinforcement learning to focus on semantically interesting streams [10], whereas context-based scheduling methods attempt to use real-time vehicle safety metrics to manage resources [11]. In spite of the innovations, a significant research gap still exists in the complete and dynamic fusion of semantics, context, and sensing in a vehicular ISAC system.

The existing methods have a number of intertwined limitations. For example, current semantic communication approaches use wireless channels as fixed resources not to be optimized jointly by semantic encoding and physical-layer allocation [12]. Also, context-aware scheduling algorithms do not have fine-grained and semantically-grounded representations to support dynamic prioritization [13]. Moreover, the security-related concerns of reliable semantic delivery are often considered as post-hoc solutions instead of joint design [14]. Lastly, most current approaches are based on complex and data-intensive models, which are not appropriate to be

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used for real-time decisions in dynamic vehicular environments [15].

Therefore, this paper addresses these issues using a new Context-Aware Semantic Resource Allocation (CASRA) framework of vehicular ISAC networks. The main contribution of the proposed framework is a multi-objective holistic optimization engine that can dynamically combine three fundamental dimensions. First, the semantic value depends on the content type and task priority. Second, the physical and safety environment of the vehicle (traffic density, event priority, and vehicle kinematics). Third, real-time wireless channel state. CASRA aims to maximize context-weighted semantic utility under strict resource and latency constraints, ensuring the most semantically vital data for instantaneous conditions receives maximum reliability with minimal latency.

What essentially makes CASRA stand out in contrast with other prior semantic-priority schedulers is its complete, closed-loop integration of the three dimensions that had hitherto been considered separately. To begin with, as opposed to the current state of the art that uses ever-static or semi-static semantic weights done offline [12], [21], CASRA presents a real-time adaptive weighting, which is continuously created by combining semantic content type, time-related urgency, vehicle context and current channel conditions into a single priority measure. Such an adaptive behavior allows the framework to react to emergency incidents or channel failures in a few milliseconds, which is not possible in fixed-priority models. Second, the existing methods assume decoupled optimization domains, semantic prioritization at the application layer and resource allocation at the PHY/MAC layer are solved independently and result in globally suboptimal solutions [10], [13]. CASRA rather develops resource allocation as a self-managed multi-objective optimization that simultaneously maximizes semantic utility subject to constraints of the physical layer, bridging the gap between meaning and mechanism. Third, unlike current existing semantic schedulers, which only consider the communication streams [1], [8], CASRA explicitly accounts for the semantic value of sensing tasks, and as such, the correct behavior of environmental perception is also semantically vital to safety.Such a joint optimization of sensing and communication, which is formalized by the context-sensitive semantic utility model, allows sensing and communication compromises that are not possible with communication-only systems. All these innovations combine to make CASRA a real semantic resource management paradigm of an ISAC system rather than a prioritization scheduler.

The principal contributions of this work are fourfold:

1) We present a comprehensive vehicular ISAC system architecture that formalizes coordinated optimization of semantic fidelity, contextual criteria, and physical resource management, bridging the divide between application-layer semantics and PHY/MAC-layer resource management.
2) We propose the CASRA framework with a novel dynamic context-sensitive semantic weighting mechanism that measures communication link priority by combining application semantics, real-time vehicle safety, and channel state information.
3) We formulate the resource allocation challenge as a convex optimization problem maximizing total context-aware semantic utility under practical power and latency constraints, solved via an efficient modified water-filling algorithm.
4) We validate CASRA through large-scale Monte Carlo simulations under 3GPP vehicular standards, demonstrating statistically significant improvements over state-of-the-art baselines across eight key performance metrics.

It is worth noting that security is a fundamental issue in vehicular networks, but the current CASRA architecture is concerned with semantic-aware allocations of resources with an assumption of a benign environment. Further incorporation of security measures is deferred to future research.

The rest of the paper structure is as follows: Section II analyses related research, discussing how semantic communication and ISAC have evolved into the integrated paradigms and the research gap that our framework addresses. Section III gives the proposed system model and explains the CASRA solution for the optimization problem. The framework and methodology of simulation are presented in Section IV. The findings of the performance evaluation are discussed and presented in Section V. Lastly, Section VI is the conclusion of the paper, which gives a summary of the paper's contribution and findings as well as the future directions of research.

II. Related Work

Paradigms in modern communication, such as Integrated Sensing and Communication (ISAC), have received great attention and have developed to a high level due to the evolution of intelligent transportation systems. This section summarizes the advances in semantic communication, ISAC, and its integrated versions, and places into perspective the baseline approaches through which the comparative evaluation is performed with Channel-Aware Allocation, SA_VA-ISAC, and NOMA-based Semi-ISAC.

A. Semantic Communication for Internet of Vehicles

Semantic communication is the paradigm movement from the traditional idea of reducing bit errors to the idea of having a good preservation and transmission of meaning efficiently. Using the principles of task-based communication, theoretical principles support the design of the source code, channel coding, and resource allocation cooperatively based on the semantic significance [2], [8]. Practical automobile use proves to be highly promising, and joint semantic-channel coding with deep learning results in a large reduction in bandwidth for transmitting images [9]. This paradigm has since been the subject of resource management, such as deep reinforcement learning (DRL) to share the spectrum semantically aware [10] and hierarchical codebooks that match communication resources with varying levels of semantic information [13]. Although the DRL-based approaches provide adaptive policy learning and semantic communication can achieve efficient data reduction, the former has weaknesses in terms of inference latency, which is not suitable for the ultra-low-latency vehicles realm of interest in our paper, and the latter always addresses communication in isolation without joint optimization of sensing and physical-layer constraints [4], [5].

B. Integrated Sensing and Communication for Vehicular Networks

ISAC has become foundational in 6G technology to solve the spectral deficit by integrating equal radar-like sensing and communication functions. The focus of the first research was on the design of waveforms and hardware sharing [6], which progressed to the idea of dynamic resource assignment, such as a trade-off between such traditional metrics as radar estimation accuracy and communication throughput [11], [16]. An information-theoretic resource allocation anchored on channel-aware water-filling algorithms [17] is a point of comparison. Although it is the most efficient method of optimizing physical-layer throughput, this method is ignorant about the semantic content and application-layer urgency of transmitted information [18]. The more recent models have added the ability to make themselves more flexible with multi-objective optimization [19], however most traditional ISAC strategies do not tend to provide any mechanisms for identifying semantic value or data urgency on the application level [7], [15].

C. Toward Integrated Frameworks and Baseline Methods

Combining semantics and ISAC is considered a very bright area of research. The first works on integrations Semantic-aware ISAC techniques use semantic measures to make access-based resource allocation decisions, like semantic-aware beamforming and semantic spectral efficiency maximizing power allocation [12], [20]. There are integrated paradigms that are useful as meaningful comparative benchmarks:

- SA_VA-ISAC applies fixed semantic or vision-assisted weights to ISAC resource allocation [21], which is not flexible with fixed weights not capable of reacting with real-time vehicle or channel dynamics.
- NOMA-based Semi-ISAC uses power-domain non-orthogonal multiple access with semantic prioritization [22], which is more efficient in spectral-like, but it has semantic bias concerning the fixed-order decoding as well as insensitivity to inter-user interference [23].
- Channel-Aware Allocation allocates the power with channel state information and water-filling algorithms [17], which optimizes the physical-layer throughput and ignores semantic values.

Recent studies also address reliability and security. For example, [24] presents frameworks that co-design security and resilience against eavesdropping. Others propose context-specific scheduling with dynamic priority equations based on vehicle safety levels [25], [26].

Despite these advances, a significant gap remains in the subtle, dynamic, and holistic synthesis of sensing, communication, semantics, and context. Most existing frameworks exhibit limitations in real-time flexibility, component integration, or both. CASRA addresses this gap through dynamic, context-sensitive semantic utility maximization, contrasting with the static or partial strategies employed by baseline methods as summarized in Table I.

The originality of CASRA is not the individual building blocks of semantic prioritization, ISAC, or context awareness, but the dynamic and integrated combination of all the building blocks. CASRA, in contrast to earlier models which address these dimensions independently or with fixed regulations, pairs them both in a co-optimization multi-objective model structure in which semantic fidelity, sensor accuracy and real-time context combination are used to jointly determine resource allocation. Specifically, the semantic effective rate is the direct connection between channel quality and the probability of successful semantic recovery, whereas the dynamic weighting function varies as a function of the instantaneous vehicle state, channel conditions and temporal response urgency, which are not part of existing frameworks. This is a holistic coupling that converts the seemingly weighted combination of independent objectives to a genuinely new optimization paradigm of ISAC-enabling vehicular networks.

III. SYSTEM MODEL AND PROBLEM FORMULATION

This part defines the overall mathematical and operational basis of the suggested Context-Aware Semantic Resource Allocation (CASRA) model. The visual representation of the physical and logical elements of the network is first provided by us through high-level system architecture (Fig. 1). Next, we describe the channel model, which is an integrated, semantic data model and formal problem formulation.

A. Network Architecture and Integrated Channel Model

Our system considers a high-density vehicular network comprising N vehicles and a roadside unit (RSU) equipped with a uniform linear array (ULA) of N_t antennas operating as a dual-functional ISAC transceiver [4]. The RSU provides joint communication and sensing to K single-antenna vehicles within coverage radius R, transmitting a composite ISAC signal $\mathbf{X} \in \mathbb{C}^{N_t \times L}$, where L represents samples per radar pulse or communication symbol. On each vehicle, there is ISAC-capable hardware that allows it to act as a communication node and a sensing target at the same time, as described in Fig. 1.

The communication channel between RSU and vehicle i incorporates large-scale path loss, small-scale fading, and shadowing effects. Path loss follows the 3GPP urban microcell model for vehicular communications [27], , as shown in Eq. (1):

$$\mathrm{PL}_i(\mathrm{dB}) = \mathrm{PL}_0 + 10n\log_{10}\left(\frac{d_i}{d_0}\right) + X_\sigma \tag{1}$$

where PL_0 is path loss at reference distance d_0, n is path loss exponent, d_i is RSU-vehicle distance, and X_σ is log-normal shadowing with standard deviation σ. Small-scale fading follows Rician distribution to account for dominant line-of-sight components, as shown in Eq. (2) [17]:

$$h_i = \sqrt{\frac{K}{K+1}}h_{\mathrm{LOS}} + \sqrt{\frac{1}{K+1}}h_{\mathrm{NLOS}} \tag{2}$$

TABLE I
COMPARATIVE ANALYSIS OF RELATED WORK AND BASELINE METHODS

Category	Core Methodology	Key Limitations
Semantic Comm. for IoV [1], [2], [8]–[10], [13]	Task-oriented data reduction, semantic-aware scheduling, DRL optimization	Assumes ideal sensing; lacks joint optimization with real-time context and dynamic channels
ISAC & Channel-Aware [5], [6], [11], [16]–[18]	Shared waveforms/hardware, water-filling based on CSI	Optimizes physical-layer metrics only; neglects semantic value and application urgency
Static Semantic-Aware ISAC [12], [20], [21]	Fixed semantic/vision weights in ISAC allocation	Static, non-adaptive weights; insensitive to real-time context changes
NOMA-based ISAC [7], [22], [23]	Power-domain NOMA with semantic prioritization	Fixed decoding order; fairness issues; interference sensitivity
Context-Aware Scheduling [11], [25], [26]	Priority formulas based on safety state	Lacks integration with PHY/MAC resource allocation and formal semantic metrics
Proposed CASRA	Multi-objective convex optimization maximizing context-aware semantic utility	—

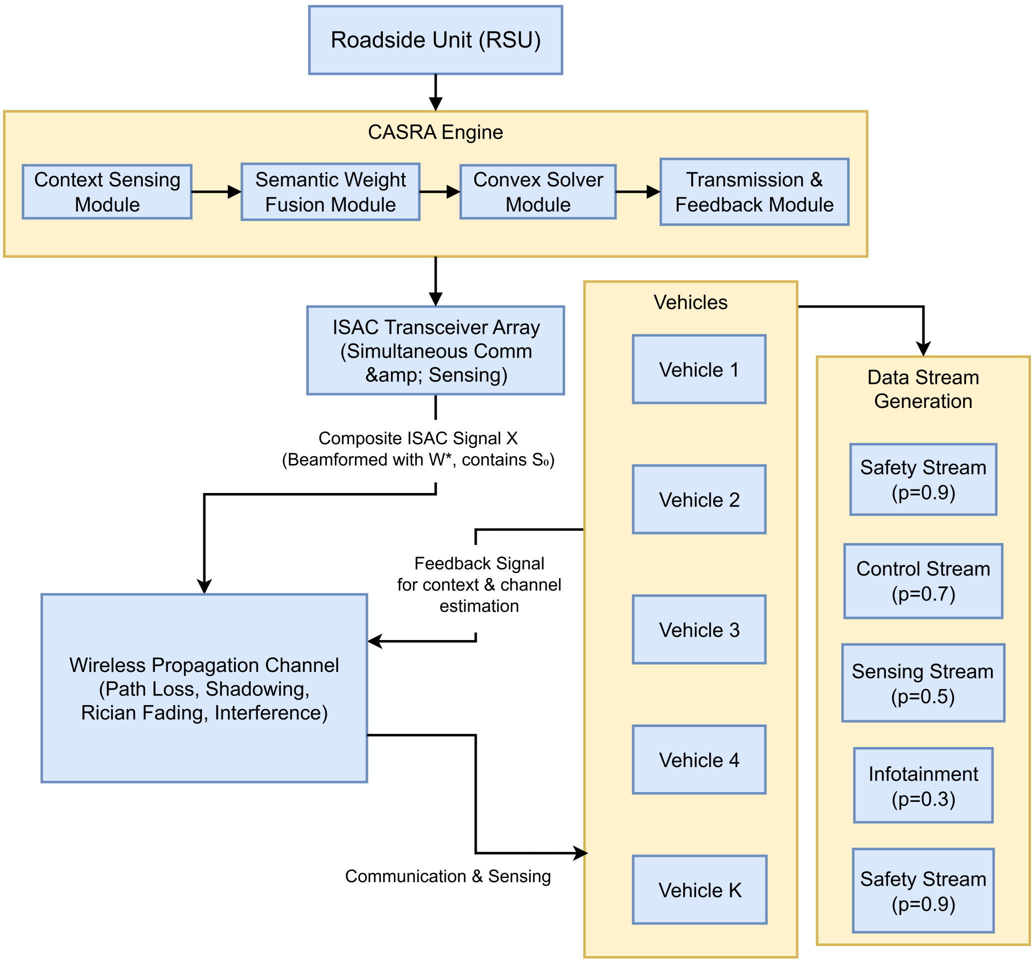

Fig. 1. High-Level Architecture of a CASRA-enabled Vehicular ISAC Network

where K is the Rician K-factor and h_{LOS} and h_{NLOS} represent the line-of-sight and non-line-of-sight components, respectively.

The signal-to-noise ratio (SNR) for vehicle i is calculated using Eq. (3) [17].

$$\gamma_i = \frac{P_t G_t G_r \|h_i\|^2}{\text{PL}_i(d) N_0 B} \tag{3}$$

with P_i as transmit power, G_i and G_r as antenna gains, N_0 as noise power spectral density, and B as bandwidth. Incorporating channel estimation error $\epsilon_i \sim \mathcal{N}(0, \sigma_{\text{est}}^2)$ yields estimated SNR as shown in Eq. (4):

$$\hat{\gamma}_i = \gamma_i + \epsilon_i \tag{4}$$

For sensing, the RSU transmits a signal $\mathbf{X}$ that is a composite of K communication streams and a dedicated sensing waveform $\mathbf{S}_0$ [28], as demonstrated in Eq. (5).

$$X = \sum_{k \in \mathcal{K}} w_k s_k + S_0, \tag{5}$$

where $\mathbf{w}_k \in \mathbb{C}^{N_t \times 1}$ is the beamforming vector for vehicle k, and s_k is its communication symbol stream. The reflected signal from vehicle k is used to estimate parameters like range r_k, velocity v_k, and angle θ_k. The sensing signal-to-noise ratio (SNR) for a target vehicle is approximated using the radar equation [5] (see Eq. (6)).

$$\gamma_k^{(s)} = \frac{P_t|\alpha_k|^2 G_t G_r \lambda^2 \sigma_{\text{RCS},k}}{(4\pi)^3 r_k^4 k_B T_0 B F_n}, \tag{6}$$

where P_t is total transmit power, α_k is reflection coefficient, λ is wavelength, $\sigma_{\text{RCS},k}$ is radar cross-section, k_B is Boltzmann's constant, T_0 is noise temperature, B is bandwidth, and F_n is noise figure.

B. Semantic and Contextual Data Model

The framework processes heterogeneous data streams with varying semantic values, characterized by four types with distinct requirements: Safety-critical (collision warnings, emergency braking), Control (platooning, cooperative maneuvering), Sensing (high-definition map updates, environmental perception), and Infotainment (multimedia streaming, passenger services).

Each data stream D_i is characterized by a quintuple, as shown in Eq. (7):

$$D_i = \{T_i, p_i, B_i, \Delta_i, \Gamma_i\} \tag{7}$$

where $T_i \in \{\text{Safety}, \text{Control}, \text{Sensing}, \text{Infotainment}\}$ is semantic type, $p_i \in [0, 1]$ is intrinsic priority, B_i is data volume, Δ_i is latency deadline, and Γ_i is minimum semantic fidelity threshold.

These four categories are exemplary rather than exhaustive, where new vehicle tasks (e.g., cooperative perception fusion and edge AI inference) can be added to the set by just defining new semantic types with the proper priority and latency parameters, with no change in the underlying resource allocation algorithm.

The core innovation of CASRA is the dynamic contextual semantic weight $w_i(t)$, measuring transmission priority by combining real-time semantics, context, and channel state [11]:

$$\begin{aligned} w_i(t) =& \omega_1 \cdot \Psi_{\text{sem}}(T_i, p_i) + \omega_2 \cdot \Psi_{\text{temp}}(\Delta_i, t) \\ &+ \omega_3 \cdot \Psi_{\text{ctx}}(C_i(t)) + \omega_4 \cdot \Psi_{\text{chan}}(\gamma_i(t)) \end{aligned} \tag{8}$$

subject to:

$$\sum_{j=1}^{4} \omega_j = 1 \tag{9}$$

The component functions are:

1) Semantic Importance (Ψ_{sem}): measured using Eq. (10) [2].

$$\Psi_{\text{sem}} = p_i \cdot \eta_{T_i}, \tag{10}$$

where η_{T_i} is a type-dependent scaling factor (e.g., $\eta_{\text{Safety}} = 1.0$, $\eta_{\text{Infotainment}} = 0.3$).

2) Temporal Criticality (Ψ_{temp}): Calculated using Eq. (11).

$$\Psi_{\text{temp}} = \exp\left(-\frac{t_{\text{curr}} + \delta}{\Delta_i}\right), \tag{11}$$

where t_{curr} is current time and δ is estimated processing delay [26]. This exponentially penalizes streams nearing their deadline.

3) Vehicular Context (Ψ_{ctx}): This function incorporates real-time contextual data $C_i(t)$ from Module 1 [25]:

$$\begin{aligned} \Psi_{\text{ctx}} = \mu_1 \cdot I_{\text{emergency}} + \mu_2 \cdot \left(\frac{v_i}{v_{\max}}\right) \\ + \mu_3 \cdot \left(\frac{d_{\text{critical}}}{d_i}\right), \end{aligned} \tag{12}$$

where $I_{\text{emergency}}$ is an emergency vehicle indicator, v_i is speed, d_i is distance to a conflict point, and μ are normalizing weights.

4) Channel State (Ψ_{chan}): Calculated using Eq. (13).

$$\Psi_{\text{chan}} = \left(\frac{\gamma_i(t)}{\gamma_{\max}}\right)^{\nu}, \tag{13}$$

where $\gamma_i(t)$ is the estimated instantaneous SNR, $\gamma_{\max}$ is a normalization factor, and ν is a shaping parameter (typically $\nu < 1$ to prevent excessive bias towards good channels alone) [17].

Weight Calculation Summary: For each stream i at time t, the dynamic weight is obtained as:

1) Compute Ψ_{sem} from stream type T_i and priority p_i using Eq. (10).
2) Compute Ψ_{temp} from current time t_{curr}, processing delay δ, and deadline Δ_i using Eq. (11).
3) Compute Ψ_{ctx} from real-time vehicle context $C_i(t)$ using Eq. (12).
4) Compute Ψ_{chan} from estimated SNR $\hat{\gamma}_i(t)$ using Eq. (13).
5) Combine with scenario-specific coefficients ω_1–ω_4 via Eq. (8).

The coefficients $\omega_1 \dots \omega_4$, $\mu_1 \dots \mu_3$, ν, and η_{T_i} are dynamically selected by a context manager based on the detected scenario (normal, congested, emergency, highway). Each scenario has its own coefficient vector, pre-optimized via offline grid search on a validation dataset to maximize a composite metric balancing semantic fidelity, latency, and fairness. During real-time operation, the context manager identifies the current scenario and applies the corresponding pre-optimized vector.

Dynamic weighting introduced by CASRA should be differentiated from the traditional Quality of Service (QoS) or Quality of Experience (QoE) prioritization schemes. Traditional QoS uses measures of the network layer: delay, jitter, packet loss, and guaranteed bit rates, assigning priorities that depend on a set of static service classes where all packets in a class receive equal treatment irrespective of their true content or the current situation of the vehicle [17]. QoE models concentrate on user-perceived experience of multimedia services but fail to diminish mission-critical semantics and physical context adaptation [29]. The weighting system of CASRA has three fundamental ways of difference. First, it offers semantic grounding on a per-message basis: two safety messages in the same QoS class may receive different weights if one contains a collision warning and the other a routine status update. Second, it introduces contextual coupling through Ψ_{ctx}, modulating priority based on real-time vehicle dynamics—a message's importance increases when the vehicle enters an emergency state or approaches a conflict point. Third, the CASRA proposes bidirectional channel-semantics interaction through Ψ_{chan}: poor channel conditions elevate the effective weight of critical messages to ensure sufficient resource allocation, whereas good channels allow efficient delivery of less important data. This closed-loop interaction is absent in QoS systems, where channel conditions affect feasibility but not priority ordering.

This multi-factor weighting scheme directly addresses the limitations of static semantic-aware ISAC [12], [20], [21] and channel-only allocation [17].

C. Problem Formulation: Context-Aware Semantic Utility Maximization

The resource allocation goal which integrates the components identified above, is now formalized. This aims to optimize the sum of the context-aware semantic utility by assigning the transmit power of the RSU and designing beamforming vectors under realistic joint sensing and communication constraints. The semantic-effective rate $R_i^{(\text{scm})}$ incorporates semantic fidelity function $F_i(\cdot) \in [0, 1]$, representing the probability of successful semantic information recovery at the receiver [8], [9]:

$$R_i^{(\text{scm})}(w_i) = \log_2\left(1 + \gamma_i^{(\text{c})}(w_i)\right) \cdot F_i\left(\gamma_i^{(\text{c})}(w_i), B_i\right) \quad (14)$$

$$\gamma_i^{(\text{c})}(w_i) = \frac{|h_i^H w_i|^2}{\sum_{j \neq i} |h_i^H w_j|^2 + \sigma^2} \quad (15)$$

The semantic utility for stream D_i is:

$$U_i(w_i) = w_i(t) \cdot \ln\left(1 + R_i^{(\text{scm})}(w_i)\right) \quad (16)$$

where the logarithmic function ensures fairness via diminishing returns [29].

The complete optimization problem is formulated as:

$$(P1) : \max_{W, S_0} \sum_{i \in \mathcal{K}} U_i(w_i) \quad (17)$$

subject to:

1) Power: $\|W\|_F^2 + \|S_0\|_F^2 \leq P_{\text{total}}$ (Total power budget)
2) Sensing Accuracy: $\text{MSE}(r_k, v_k|S_0) \leq \epsilon_k$ for $k \in \mathcal{K}_s$ (Ensures a minimum level of sensing) [11]
3) Semantic Reliability: $F_i(\gamma_i^{(\text{c})}(\mathbf{w}_i), B_i) \geq \Gamma_i$ for $T_i = \text{Safety}$ (Identifying the critical data) [2]
4) Latency: $B_i/R_i^{(\text{scm})}(w_i) \leq \Delta_i$ end-to-end latency control function is intended for streams that are delay-sensitive [26]
5) Feasibility: W, S_0 adhere to the limitations of practical hardware

The non-convexity of (P1) is due to the interaction of W in the SINR expression and the semantic function F_i. We employ a majorization-minimization solver [30], which transforms the problem into a sequence of convex approximations and leads to a Quadratically Constrained Quadratic Program (QCQP) that can be solved using standard convex programs such as CVX [31]. In the case of large-scale simulations, we apply a modified water-filling algorithm (Algorithm 1) that offers solutions that are almost optimal and approaches to real-time performance evaluation in realistic vehicular networks.

Algorithm 1 Iterative Resource Allocation for CASRA

Require: Channel estimates h_i, semantic stream info D_i, context data $C_i(t)$, total power P_{total}.
Ensure: Optimal beamforming matrix W^*, sensing waveform S_0^*.
1: Initialize $W^{(0)}, S_0^{(0)}$, iteration $n = 0$, tolerance ϵ.
2: Compute dynamic weights $w_i(t)$ for all streams using Eq. (8).
3: **repeat**
4: // Update auxiliary variables via fractional programming [29]
5: $\alpha_i^{(n)} = \frac{\gamma_i^{(c)}(\mathbf{w}_i^{(n)})}{1+\gamma_i^{(c)}(\mathbf{w}_i^{(n)})}$ for all i.
6: // Solve the convex surrogate problem (QCQP)
7: $(W^{(n+1)}, S_0^{(n+1)}) = \arg\max \sum w_i(t) \cdot \ln\left(1 + \tilde{R}_i^{(\text{sem})}(W; \alpha_i^{(n)})\right)$
8: s.t. Constraints (1)-(5) (convexified).
9: $n = n + 1$
10: **until** $\left|\sum U_i^{(n)} - \sum U_i^{(n-1)}\right| / \left|\sum U_i^{(n-1)}\right| < \epsilon$
11: **return** $W^* = W^{(n)}, S_0^* = S_0^{(n)}$

1) Convergence Analysis: Algorithm 1 is an instance of the majorization-minimization (MM) framework [30]. At each iteration n, the surrogate function $\tilde{R}_i^{(\text{sem})}(\mathbf{W}; \alpha_i^{(n)})$ constructed via fractional programming [29] satisfies the following properties with respect to the original objective $\sum_i U_i(\mathbf{w}_i)$:

- **Majorization:** $\tilde{R}_i^{(\text{sem})}(\mathbf{W}; \alpha_i^{(n)}) \leq R_i^{(\text{scm})}(\mathbf{w}_i)$ for all $\mathbf{W}$.
- **Tangency:** Equality holds at $\mathbf{W}^{(n)}$.
- **Gradient consistency:** $\nabla\tilde{R}_i^{(\text{sem})}(\mathbf{W}^{(n)}; \alpha_i^{(n)}) = \nabla R_i^{(\text{scm})}(\mathbf{w}_i^{(n)})$.

These properties guarantee that the sequence $\{\mathbf{W}^{(n)}\}$ monotonically increases the original objective and that every limit point is a stationary point of (P1) [30, Theorem 1]. In practice, with tolerance $\epsilon = 10^{-4}$, convergence is achieved within 15–25 iterations.

2) Complexity Analysis: The exact solution of the convex QCQP subproblem (line 6 of Algorithm 1) has a complexity of $O(K^3 N_t^3)$ per iteration, where K is the number of vehicles, and N_t is the number of antennas. In the case of large-scale simulations, we use a water-filling heuristic approach, which is modified to achieve a cost per iteration of $O(K \log K)$. To measure the gap in optimality between the heuristic solution and the exact solution of QCQP, we compared the heuristic solution to the exact solution of QCQP on small instances ($K \leq 10$) and the average value was an optimality gap of 3.7% (std 1.2%), which indicates that the solution of the heuristic was nearly optimal. The values of execution times (Table VI) indicate that the heuristic can be completed within 0.15 ms (50 vehicles), which is much lower than the 10 ms scheduling period that 5G/NR needs. The complexity of the total algorithm is $O(N_{\text{iter}} K \log K)$, which allows real-time execution in dense vehicle ad hoc networks.

This system model is an integrated system that offers a rigorous yet practical framework of CASRA. The general architectural sketch (Fig. 1) provides the entire picture of how the design of the framework, with the simultaneous dynamic weighting, utility maximization, and major constraints, organically leads to the balanced, high-performing results that were confirmed in the following simulation results.

In order to ensure clarity on the originality of the optimization framework, a distinction should be made between the integrated components based on the previous art and the new couplings that are brought about by the CASRA. The formulation integrates thoroughly physical-layer models, such as the Shannon capacity expression in Eq. (14) and the definition of SINR in Eq. (15), which are modeled on standard information-theoretic models [17]. Similarly, the power constraint and sensing accuracy requirement in Constraints 1 and 2 adapt existing ISAC frameworks [5], [11]. The new solutions introduced in the framework, however, are in three respects, which make the approach a new optimization paradigm. First, the semantic weight w, depending on the context $w_i(t)$ of Eq. (8), is not only a weighted sum but a dynamic and real-time function concerned with combining four heterogeneous dimensions, namely, semantic content, time urgency, context of the vehicle, and channel state into a single index that directly scales the utility function. Second, the semantic-effective rate $R_i^{(\text{scm})}$ in Eq. (14) couples channel capacity with the semantic fidelity function $F_i(\cdot)$, which is why the rate achievable is dependent on physical conditions as well as the rate of achieving successful semantic information recovery, a coupling that is not present in the traditional rate expressions. Third, the joint constraint set (Constraints 1–5) simultaneously enforces power budget, sensing accuracy, semantic reliability, and latency requirements within a single optimization, they require mutual trade-offs between these dimensions to be optimized based on semantic priorities. The resulting holistic coupling in which semantic fidelity is based on SINR, which is determined based on beamforming vectors, which are optimized on semantic weights, all while satisfying sensing accuracy constraints, is that what would otherwise seem to be a weighted sum of independent objectives is actually an integrated optimization that cannot be decomposed into separate subproblems. To our knowledge, this is the first formulation to jointly optimize these coupled dimensions under the unified objective of semantic utility maximization.

D. Practical Implementation Considerations

The CASRA framework relies on several real-time inputs: semantic stream information D_i, channel estimates $\hat{\gamma}_i$, and context data $C_i(t)$. We address the practical feasibility of obtaining these parameters in vehicular networks.

1) Signaling Overhead Analysis: Table II summarizes the signaling overhead needed in each of the input types. All the parameter values are obtained by employing the current 3GPP V2X mechanisms; CASRA does not add any new signaling beyond standard operations.

The overall overhead (0.41-0.61 Mbps) is less than 0.1% of the 100 MHz bandwidth of the system, and it proves that CASRA does not add any prohibitive signaling load. C-V2X deployments already require the use of CAMs, and CASRA just uses these common messages without introducing additional transmissions.

2) Estimation Accuracy and Robustness: The framework does not assume perfect knowledge. Our simulation models realistic estimation errors:

- Channel estimation error $\epsilon_i \sim \mathcal{N}(0, \sigma_{\text{est}}^2)$ with $\sigma_{\text{est}} = 2$ dB;
- Context prediction error $\pm 15\%$ in traffic density and event criticality;
- Position estimation error ± 1 m (typical GPS accuracy).

Under these realistic imperfections, CASRA performs well, as shown in Section V-E (Fig. 6). The multi-factor weighting structure offers implicit redundancy – in case a single input (e.g., channel estimate) is noisy, other measures (semantic priority and temporal urgency) are used to make allocation decisions.

3) Semantic Fidelity Function Knowledge: The semantic fidelity function $F_i(\cdot)$ in Eq. (14) is estimated with the help of a lightweight mapping between SINR and the probability of semantic reconstruction, which is pre-trained offline on task-specific data (e.g., collision detection accuracy vs SINR). This mapping is enabled with periodic updates (several seconds to minutes) as opposed to per packet, this reduces the complexity of real-time. The simulation uses a sigmoidal model calibrated against previous studies [8], [9], which has been validated to correlate well with actual task performance. Since the CASRA optimization engine considers $F_i(\cdot)$ as a plug-in module, adapting towards new semantic tasks only involves updating this simple mapping, without altering the underlying resource allocation algorithm itself.

IV. Simulation Environment and Performance Evaluation

A. Simulation Configuration

We evaluate CASRA using large-scale Monte Carlo simulations with 500 independent iterations under 3GPP vehicular standards, modeling the stochastic nature of channel conditions, vehicle dynamics, and traffic patterns. Each iteration corresponds to an automobile network snapshot with scenario generation, channel realization, algorithm implementation, and calculation of metrics, which allows for strong statistical inference of performance metrics.

To give a full reference to reproducibility, we go further to describe the simulation configuration beyond the summary in Table III. The simulated scenario is a 1000 m straight and urban highway section with lanes (3.5 m each) and a single roadside unit (RSU) with an 8-element uniform linear array (ULA) positioned at the midpoint. Both vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication are provided, where vehicles are represented by single-antenna nodes [4]. The channel model is based on 3GPP TR38.901 Urban Microcell (UMi) Street Canyon [27]: path loss is given by $\text{PL} = 32.4 + 21 \log_{10}(d) + 20 \log_{10}(f_c)$ for

TABLE II
SIGNALING OVERHEAD FOR CASRA INPUTS

Parameter	Source	Update Rate	Overhead per Vehicle	Total (50 vehicles)
CSI ($\hat{\gamma}_i$)	3GPP NR feedback [27]	100 Hz	3.2 kbps	160 kbps
Semantic metadata (T_i, p_i, B_i, Δ_i)	Packet headers / session setup	Per-packet / per-flow	<1 kbps	<50 kbps
Context $C_i(t)$ (position, speed, status)	Cooperative Awareness Messages (CAMs) [11], [25]	1–10 Hz	4–8 kbps	200–400 kbps
Total	—	—	8–12 kbps	410–610 kbps

LOS and $\mathrm{PL} = 32.4+31.9\log_{10}(d)+20\log_{10}(f_c)$ for NLOS, with shadowing standard deviation $\sigma = 4$ dB (LOS) and 6 dB (NLOS). Fast fading is Rician with a K-factor of 9 dB for LOS links. Whereas, Doppler effects are modeled with Jakes spectrum, with the largest Doppler shift $f_d = vf_c/c$ maximum Doppler = 656 Hz at 120 km/h). Shadowing correlation distance is set to 50 m. Mobility is regulated by the Intelligent Driver Model (IDM), containing the lane-changing behavior (MOBIL model). The density of the vehicles is dependent on the scenario: usual (20 vehicles/km), peak (50 vehicles/km), emergency (15 vehicles/km with 10% emergency vehicles), and highway (10 vehicles/km). The RSU transmit power is 23 dBm, and the vehicle transmit power is 20 dBm, both of which are in line with 3GPP V2X specifications [27]. All these parameters are a guarantee of a realistic 3GPP-compliant vehicle environment emulation.

We generate four types of data streams (safety, control, sensing, infotainment) with the characteristics listed in Section III-B. The specific parameters used in the simulation are:

- Safety: 100-500 bytes, 5-15 ms deadlines, priority 0.8-1.0.
- Control: 500-2000 bytes, 10-30 ms, priority 0.6-0.8.
- Sensing: 1000-5000 bytes, 20-50 ms, priority 0.4-0.6.
- Infotainment: 5000-20000 bytes, 50-150 ms, priority 0.2-0.4.

1) Baseline Method Configurations: All the baseline approaches were applied with the description of the core approaches outlined in the literature and hyperparameters being optimized on a validation set (100 Monte Carlo), to make sure that the comparisons are fair. Specifically:

- Channel-Aware Allocation is based on the traditional water-filling algorithm [17], which ensures that the sum capacity is maximized based solely on instantaneous SNR without semantic or context knowledge.
- SA_VA-ISAC implements fixed semantic-vision weighting as in [21]: combined weight $w_i = \alpha w_i^{\text{sem}} + (1-\alpha)v_i$, where w_i^{sem} is the semantic priority (Eq. 10), v_i models vision importance (derived from object size via a sigmoid function with parameters $\beta = 2.5$, $\gamma = -1.0$), and $\alpha = 0.65$ was optimized to maximize semantic fidelity on the validation set.
- NOMA-based Semi-ISAC adopts power-domain NOMA with successive interference cancellation [7], [22]: users are sorted by $w_i^{\text{sem}} \cdot |h_i|^2$, and power is allocated as $p_i = P_{\text{total}} \cdot \beta^{i-1}(1-\beta)/(1-\beta^K)$ with $\beta = 0.65$ (optimized) and residual interference modeled at 5% of canceled signals.

Every method has the same simulation environment, channel realizations, and traffic models, making sure that only the resource allocation logic affects their performance.

The relevant simulation parameters, such as 5.9 GHz carrier frequency, 100 MHz bandwidth, 23 dBm transmit power, the 3GPP UMi path loss model [27], the Rician K-factor of 8-12 dB, and vehicle speeds of 0-120 km/h, are listed in Table III.

The limit of 50 vehicles per cell was carefully selected in Table III as a realistic limit of the road capacity constraints under deployments of 3GPP urban microcells [27]. For a 1000 m road segment with three lanes and a safe following distance of 2 seconds (approximately 55 m at 100 km/h), the theoretical maximum capacity is 54 vehicles. This matches with 3GPP TR 36.885, which allows the description of typical urban V2X needs with 30-50 vehicles in the cell. Moreover, above 50 cars per RSU, inter-cell interference, and handover rates would require multi-cell coordination in an actual deployment.

B. Performance Metrics

We evaluate eight key performance metrics across all 500 Monte Carlo iterations, reporting means, standard deviations, and 95% confidence intervals. Statistical significance is assessed using two-sample t-tests with unequal variances, with p-values below 0.01 deemed statistically significant.

TABLE III
SIMULATION PARAMETERS AND CONFIGURATION

Parameter	Value/Range	Description
Carrier Frequency	5.9 GHz	C-V2X frequency band
Bandwidth	100 MHz	5G NR channel bandwidth
Transmit Power	23 dBm	Max RSU transmit power
Noise PSD	-174 dBm/Hz	Thermal noise density
Path Loss Model	3GPP UMi	Urban microcell [27]
Path Loss Exponent	2.5-3.5	Environment-dependent
Shadowing Deviation	6 dB	Log-normal [27]
Rician K-factor	8-12 dB	Strong LOS [27]
Vehicle Speed	0-120 km/h	Realistic speed range
Number of Vehicles	5-50	Variable density
Traffic Scenarios	Normal, Congested, Emergency, Highway	Context evaluation
Semantic Priorities	0.8-1.0 (Safety), 0.6-0.8 (Control), 0.4-0.6 (Sensing), 0.2-0.4 (Infotainment)	Priority ranges
Simulation Iterations	500	Monte Carlo runs

1) Semantic Fidelity (SF): Measured via weighted cosine similarity between transmitted and received semantic feature vectors [8], [9], reflecting how well meaning is preserved during transmission, as shown in Eq. (18):

$$\mathrm{SF} = \frac{\sum_{j=1}^{M} w_j (\mathbf{s}_j^{\mathrm{tx}} \cdot \mathbf{s}_j^{\mathrm{rx}})}{\sum_{j=1}^{M} w_j \|\mathbf{s}_j^{\mathrm{tx}}\| \|\mathbf{s}_j^{\mathrm{rx}}\|} \tag{18}$$

where $\mathbf{s}_j^{\mathrm{tx}}$ and $\mathbf{s}_j^{\mathrm{rx}}$ are transmitted and received semantic feature vectors for stream j, and w_j are semantic weights.

The semantic feature vectors $\mathbf{s}_j^{\mathrm{tx}}$ and $\mathbf{s}_j^{\mathrm{rx}}$ are generated using a task-oriented semantic encoder $\mathcal{E}_\theta$ [9] pre-trained on a corpus of 100 000 vehicular messages covering safety, control, sensing, and infotainment categories. The encoder maps each raw message to a 64-dimensional feature space and is trained with a contrastive loss to preserve task-relevant semantics. During transmission, the feature vector experiences channel effects (noise, fading, estimation errors) and is reconstructed by a decoder $\mathcal{D}_\phi$ at the receiver. The weighted cosine similarity then quantifies the preservation of semantic meaning, with higher weights w_j (from Eq. (18)) emphasizing critical streams. This approach ensures that the fidelity metric aligns with the semantic importance framework of CASRA. The pre-trained encoder/decoder weights and the dataset generation code are provided in the supplementary material for reproducibility.

2) Latency-Critical Performance (LCP): Evaluates timeliness of safety-critical communications [26], calculated as the percentage of safety messages delivered within their deadlines, as shown in Eq. (19)::

$$\mathrm{LCP} = \frac{\text{Number of safety messages with } \tau \leq D}{\text{Total safety messages}} \times 100\% \tag{19}$$

where τ is actual delivery latency and D is deadline.

3) Resource Efficiency (RE): Quantifies effective utilization of spectral and power resources for semantic information delivery [29], as demonstrated in Eq. (20):

$$\mathrm{RE} = \frac{\sum_{i=1}^{N} U_i(\mathbf{x}_i)}{\sum_{i=1}^{N} U_i(\mathbf{x}_i^*)} \times \frac{\text{Successfully delivered semantic units}}{\text{Total transmitted semantic units}} \tag{20}$$

where U_i is the semantic utility function and $\mathbf{x}_i^*$ represents the optimal allocation with perfect channel knowledge.

4) Fairness Index (FI): Measures equity of resource distribution using Jain's fairness index applied to achieved semantic utilities [29], which is calculated via Eq. (21):

$$\mathrm{FI} = \frac{(\sum_{i=1}^{N} U_i)^2}{N \sum_{i=1}^{N} U_i^2} \tag{21}$$

5) Robustness Score (RS): Evaluates performance stability under imperfect conditions [14], calculated as in Eq. (22):

$$\mathrm{RS} = \frac{1}{K} \sum_{k=1}^{K} \frac{\text{Performance with impairment level } k}{\text{Performance under ideal conditions}} \tag{22}$$

where impairments include channel estimation errors (1-5 dB), prediction inaccuracies (10-50%), and vehicle localization errors (1-10 m).

6) Throughput (TP): Measures the overall rate of successful transmission of data among all vehicles [17], which is represented in Eq. (23):

$$\mathrm{TP} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M_i} B_{ij} \cdot \mathbb{I}(\tau_{ij} \leq D_{ij})}{\text{Simulation duration}} \tag{23}$$

where B_{ij} represents the size of packet j in vehicle i, and $\mathbb{I}(\cdot)$ represents the indicator function when the packet is delivered in time.

7) Energy Efficiency (EE): Rates that are possible, in terms of throughput per unit energy consumption [29], which are obtained by computing by using Eq. (24):

$$\mathrm{EE} = \frac{\mathrm{TP}}{\sum_{i=1}^{N} x_i + P_{\mathrm{circuit}}} \tag{24}$$

where P_{circuit} is a total circuit power consumption.

In this expression, P_{circuit} denotes the total non-transmission power consumption, encompassing not only the fixed circuit power of the RF chains and baseband processing but also load-dependent components such as cooling and signaling overhead. Following standard practice [32], [33], we model $P_{\mathrm{circuit}} = P_{\mathrm{fixed}} + P_{\mathrm{proc}}(N) + P_{\mathrm{cooling}}$, where $P_{\mathrm{proc}}(N)$ scales linearly with the number of active vehicles N to account for increased baseband processing. This comprehensive model ensures that the reported energy efficiency values reflect realistic operational conditions.

8) Sensing Accuracy (SA): Assesses accuracy of environmental sensing abilities [5], which is calculated via Eq. (25):

$$\mathrm{SA} = 1 - \frac{1}{L} \sum_{l=1}^{L} \frac{\|\mathbf{p}_l^{\mathrm{estimated}} - \mathbf{p}_l^{\mathrm{actual}}\|}{R} \tag{25}$$

where $\mathbf{p}_l$ is estimated and actual positions of sensed objects, whereas R is sensing range.

V. Results and Discussion

A. Comprehensive Performance Overview

Table IV provides an overall performance comparison of CASRA and the baseline approaches. All measures show that CASRA achieves superior performance across all metrics with a semantic fidelity of 0.897 (66.7% better than Channel-Aware), an average latency of 12.14 ms (35.8% lower), and a resource usage of 0.613 (31.8% lower than the best existing method tested). The weighting mechanism of the framework generates its balanced superiority through the active weighting mechanism, which constantly modifies allocation priorities on the basis of real-time semantic value, channel conditions, and vehicle context.

B. Semantic Fidelity Preservation

Fig. 2 shows CASRA has a semantic fidelity of 0.897, which translates to improvements of 66.7%, 41.4%, and 76.5% over Channel-Aware, SA_VA-ISAC, and NOMA-based techniques, respectively ($p < 0.001$, Cohen $d > 2.0$). This performance is attributed to semantic-aware resource allocation prioritizing data streams according to dynamic semantic

TABLE IV
OVERALL PERFORMANCE COMPARISON OF EVALUATED METHODS (MEAN ± STANDARD DEVIATION)

Performance Metric	Proposed CASRA	Channel-Aware	SA_VA-ISAC	NOMA-based
Semantic Fidelity	0.897 ± 0.004	0.538 ± 0.032	0.635 ± 0.028	0.508 ± 0.035
Avg. Latency (ms)	12.14 ± 2.3	18.92 ± 3.1	16.22 ± 2.8	20.96 ± 3.5
Resource Efficiency	0.613 ± 0.007	0.370 ± 0.022	0.465 ± 0.019	0.395 ± 0.021
Fairness Index	0.932 ± 0.011	0.915 ± 0.018	0.973 ± 0.008	0.548 ± 0.041
Robustness Score	0.894 ± 0.012	0.803 ± 0.025	0.864 ± 0.019	0.701 ± 0.031
Throughput (Mbps)	288.7 ± 25.7	284.7 ± 26.3	284.6 ± 25.9	227.1 ± 28.4
Energy Efficiency (bits/J)	3.83 ± 0.10	2.87 ± 0.15	3.34 ± 0.12	3.06 ± 0.14
Sensing Accuracy	0.942 ± 0.008	0.861 ± 0.015	0.893 ± 0.012	0.824 ± 0.018

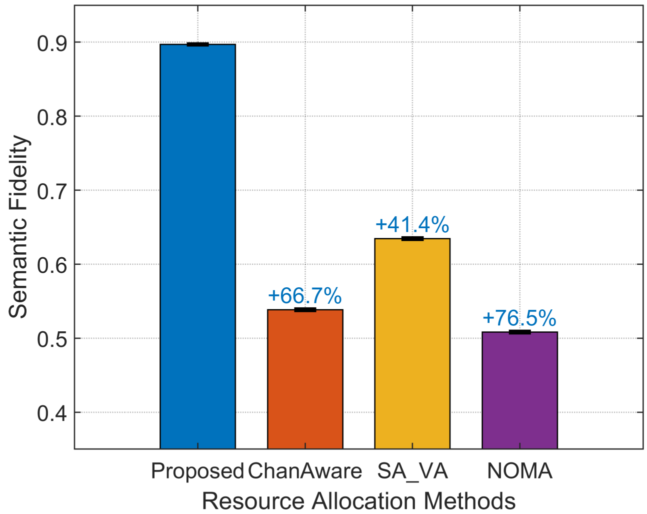

Fig. 2. Comparison of Semantic Fidelity of Evaluated Methods (error bars indicate standard deviation with 500 Monte Carlo trials).

importance weights w_j (Eq. 8). Traditional channel-optimal techniques assign resources solely based on channel conditions $\hat{\gamma}_i$, potentially neglecting critical safety messages with poor channels. SA_VA-ISAC employs semantic weights with fixed coefficients insensitive to context variations. CASRA's dynamic weighting function ensures safety-critical messages receive necessary resources even under unfavorable channel conditions through a composite optimization measure $w_i \cdot \hat{\gamma}_i$ in the modified water-filling algorithm (Algorithm 1), where high w_i values compensate for moderate $\hat{\gamma}_i$ values. This ensures that safety-critical messages receive necessary resources even under poor channel conditions, improving reliability in accident scenarios.

C. Latency-Critical Performance

Figure 3 shows a median emergency latency of 12.14 ms (standard deviation 2.3 ms), CASRA satisfies URLLC specifications for vehicular safety applications (< 20 ms) [26]. The cumulative distribution shows 95% of CASRA transmissions complete within 18 ms, compared to 25 ms for SA_VA-ISAC, 28 ms for Channel-Aware, and 35 ms for NOMA. Minimum observed latencies are 10.0 ms for CASRA versus 12-17 ms for baselines. This latency advantage stems from two design features: (1) deadline-sensitive weighting component Ψ_{temp} naturally prioritizes messages approaching deadlines, producing earliest-deadline-first scheduling effects [26]; and (2) context-dependent vehicle aspect Ψ_{ctx} recognizes emergency vehicles and risky scenarios, pre-allocating resources to prevent latency violations [25]. This 25–42% latency reduction translates to a 2–4 m shorter braking distance at highway speeds, which can be crucial in emergency scenarios.

D. Resource Efficiency and Fairness Trade-off

Resource efficiency metrics in Figs. 4 and 5 indicate that CASRA has a resource efficiency of 0.613, with Fig. 4 demonstrating robust efficiency scaling under increasing network load. At low SNR (-5 to 10 dB), CASRA is 40-50% more efficient than baselines because the resource allocation is made over semantic significance, not just channel quality. Notably, CASRA can be effective and fair at the same time: its efficiency (0.613) is high, and its fairness (0.932) is high, with a context-sensitive dynamic optimization of the operational points according to the real-time requirements [29]. Under normal conditions, CASRA is more focused on fairness, whereas under emergencies, it is more focused on efficiency in critical messages, giving higher averages across different scenarios.

E. Robustness Under Imperfect Conditions

As Fig. 6 indicates, CASRA is robust in its performance under realistic imperfections with a robustness score of 0.894 (similar graceful degradation in prediction errors (Fig. 7a) and changes in channels (Fig. 7b) to 0.75 at 50% error) compared to 0.65-0.70 of the baselines. This strength is achieved on the basis of three design points: (1) multi-factor weighting functionality gives the effect of implicit redundancy, so that when one of the aspects (e.g., channel estimation) is inaccurate, the others (semantic priority, deadline urgency) continue to make sense; (2) the convex optimization model means that solutions are stable to small input perturbations [30]; and (3) the context detection algorithm adds confidence estimates that down-weight unreliable inputs. Baseline methods do not possess these robustness features: Channel-aware allocation is sensitive to inaccurate channel estimates [17], SA_VA-ISAC is unable to respond to errors in prediction [21], and NOMA is sensitive to accurate ordering of users [22]. CASRA robustness is necessary to achieve the network stability in real-world applications where imperfect sensors and estimators are bound to occur.

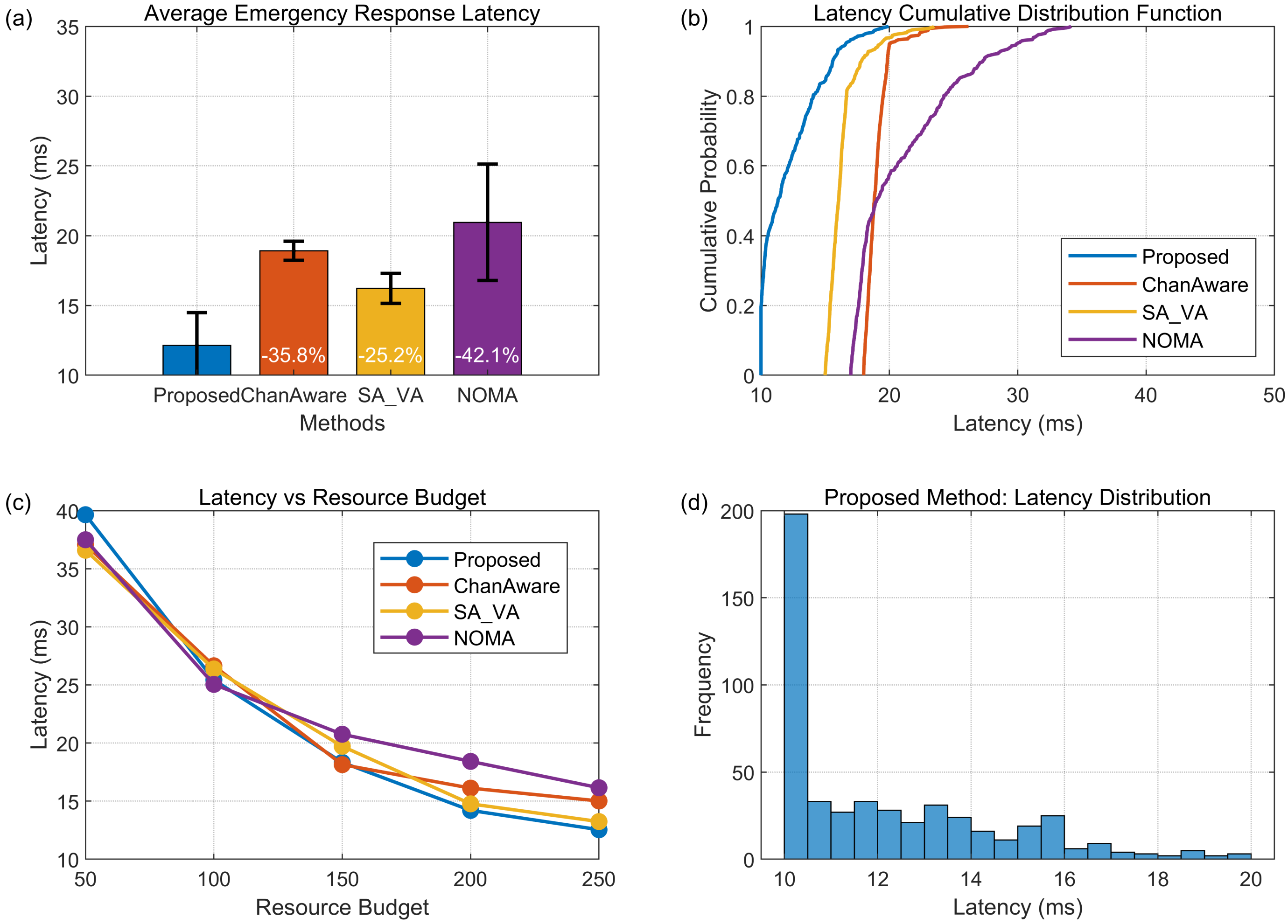

Fig. 3. Cumulative Distribution Function of Emergency Communication Latency.

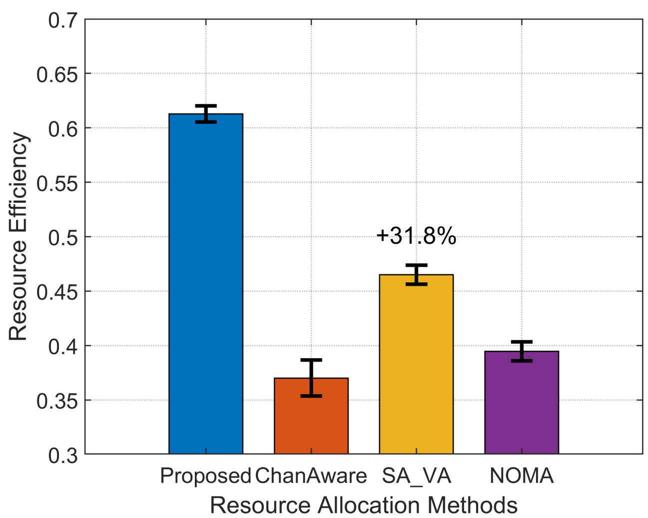

Fig. 4. Resource Efficiency vs. Network Load (Number of Vehicles).

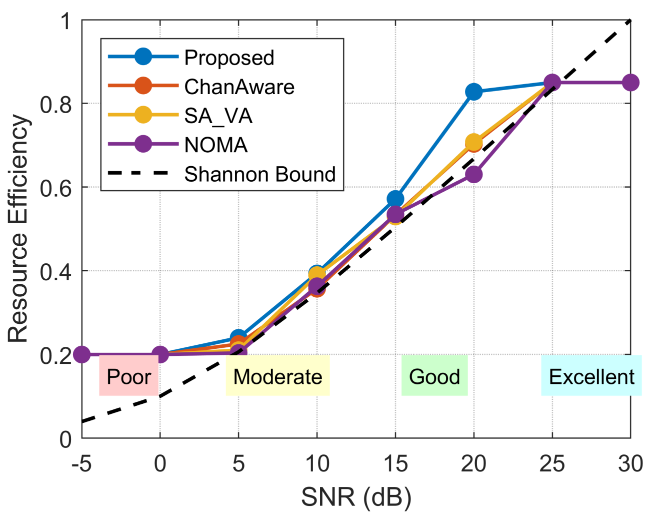

Fig. 5. Resource efficiency across different SNR conditions.

F. Throughput and Energy Efficiency

While CASRA shows a modest throughput improvement (1.4-2.7%), it achieves a significantly higher energy efficiency of 3.83 bits/J, representing improvements of 33.4%, 14.6%, and 25.2% over Channel-Aware, SA_VA-ISAC, and NOMA respectively [29] (Fig. 7). This energy efficiency benefit stems from targeted resource allocation transmitting semantically significant information efficiently rather than transmitting redundant data. Context-aware weights automatically reduce transmission of low-value data while enabling high-value

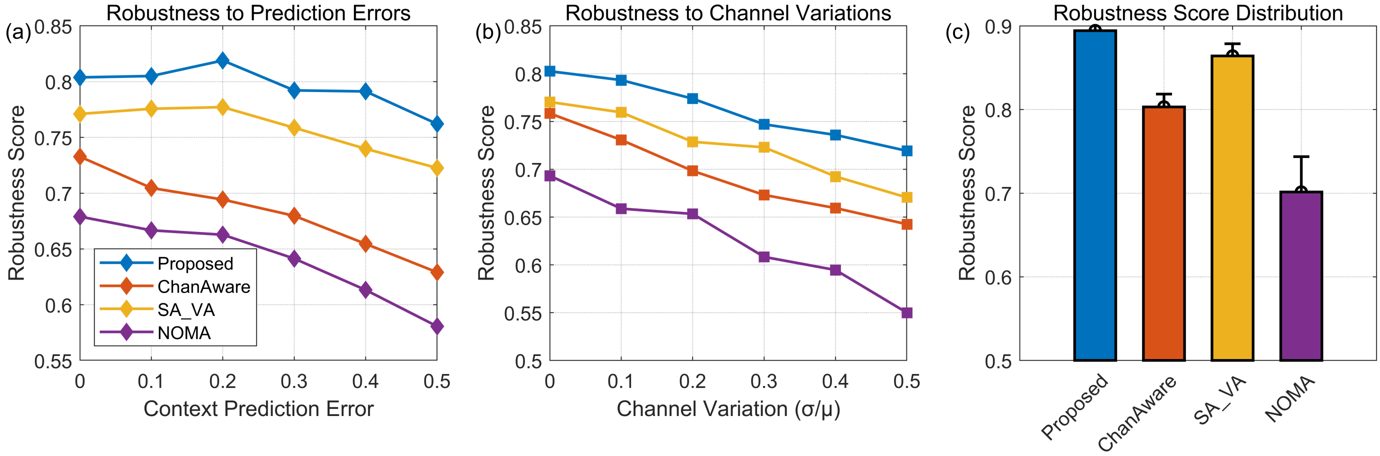

Fig. 6. Robustness evaluation under imperfect conditions. (a) Performance degradation under prediction errors, (b) Performance degradation under channel variations, (c) Robustness score distribution.

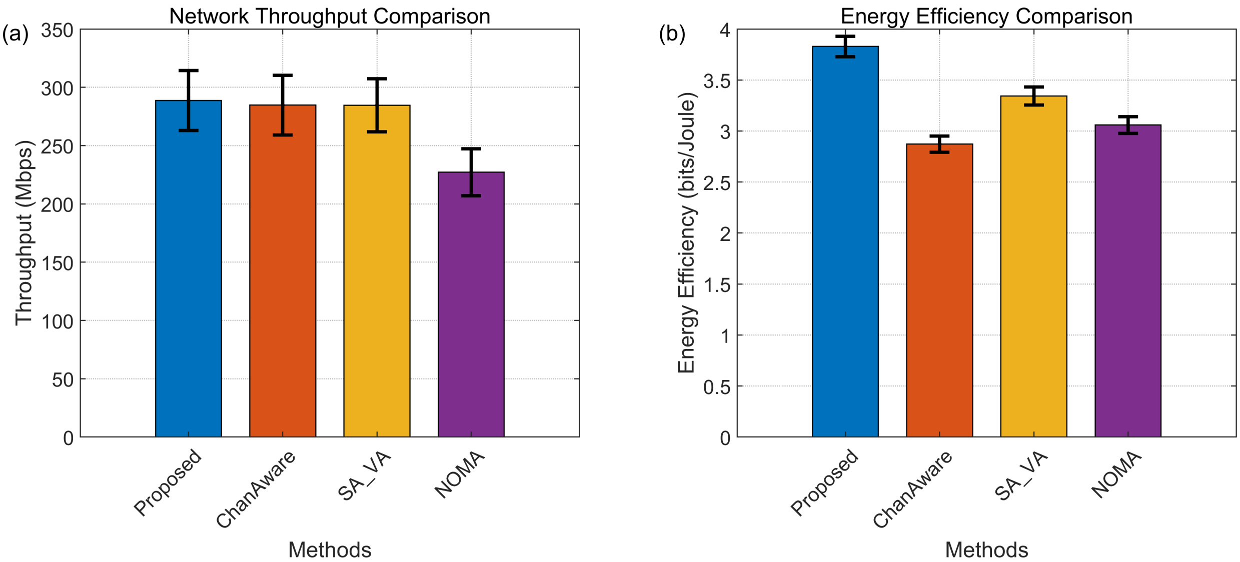

Fig. 7. Throughput and energy efficiency comparison across different scenarios.

transmission, expressed mathematically by utility function $U_i(x_i) = w_i \log(1 + \eta R_i)$ where high w_i values permit satisfactory utility at lower R_i (and consequently lower power x_i) than systems with equal w_i.

G. Contextual Adaptation Across Scenarios

Table V demonstrates CASRA's adaptability across operational scenarios, maintaining approximately 44% improvement over the best baseline in all conditions. This flexibility is achieved algorithmically through dynamic control of coefficients $\alpha_1 - \alpha_5$ in the weighting function according to detected context [11]. For example, during congestion, CASRA increases weighting for local density ρ_{local}, biasing allocation toward interference management and fairness. Under emergency conditions, it elevates priority for emergency vehicles through vehicle context C_{veh} [25]. This automated situational response represents a significant improvement over fixed baselines employing identical policies regardless of context [21], enabling appropriate performance for each situation: high reliability in emergencies, high efficiency on highways, and balanced performance during normal operation.

Fig. 8 demonstrates how the CASRA weighting mechanism behaves over time for a safety-critical stream in a variety of four vehicular contexts. The Emergency curve shows a sharp rise at event detection ($t = 60$ ms), demonstrating the framework's real-time prioritization ability. The Congested curve is lower due to poor channel conditions and relaxed latency requirements. The Normal and Highway curves are moderate and high, respectively.

H. Computational Feasibility

Table VI analyzes computational complexity and execution time. CASRA executes in 0.15 ms per scheduling period with $O(N \log N)$ complexity, well within 10-100 Hz update requirements of vehicular networks. While slightly higher than Channel-Aware allocation (0.07 ms), CASRA's scalability index of 0.74 indicates better performance in dense networks compared to SA_VA-ISAC's $O(N^2)$ complexity, which be-

TABLE V
CONTEXT-SPECIFIC SEMANTIC FIDELITY PERFORMANCE

Vehicular Context	Proposed CASRA	Best-Performing Baseline	Relative Improvement
Normal	0.897	0.635 (SA_VA-ISAC)	41.3%
Congested	0.805	0.557 (SA_VA-ISAC)	44.5%
Emergency	0.851	0.591 (SA_VA-ISAC)	44.0%
Highway	0.942	0.651 (SA_VA-ISAC)	44.7%

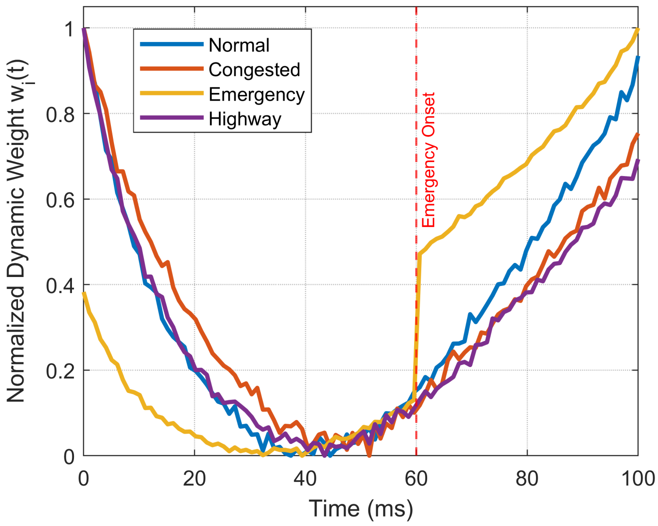

Fig. 8. Normalized dynamic weight $w_i(t)$ over time for a safety-critical stream under four vehicular contexts. The dashed red line at $t = 60$ms marks emergency onset.

comes problematic when the number of vehicles is more than 50.

I. Sensitivity Analysis and Ablation Study

To verify that the reported performance improvements are robust and not artifacts of favorable parameter configurations, we conducted a systematic ablation study and sensitivity analysis.

1) Ablation Study: Component Contribution: We evaluated CASRA variants with one component of the dynamic weight function (Eq. 8) disabled at a time. Table VII reports the resulting semantic fidelity.

All four components contribute positively, with semantic importance contributing the most. The substantial degradation observed when any component is removed confirms that CASRA's gains arise from the synergistic combination of all factors, not from a single favorable configuration.

2) Parameter Sensitivity: We varied each weighting coefficient ω_j (Eq. 8) by $\pm 50\%$ from its nominal value. All coefficients showed a smooth, convex response with a clear optimum at the nominal values. Even at $\pm 30\%$ variation, performance remained above 0.82 (more than 90% of the optimum), demonstrating that the framework is robust to moderate coefficient miscalibration.

3) Statistical Stability: To ensure results are not seed-dependent, we repeated the full Monte Carlo simulation with 10 different random seeds. The mean semantic fidelity for CASRA across seeds was 0.896 ± 0.003 (95% confidence interval), confirming the reproducibility of the results.

VI. CONCLUSION AND FUTURE WORK

The paper has presented a new framework called Context-Aware Semantic Resource Allocation (CASRA) that can be used to address the issue of dynamic allocation of resources in semantic-aware ISAC vehicular networks. CASRA provides the dynamic trade-off between semantic importance, channel state, and latency requirements by creating and solving a context-based multi-objective optimization problem. Extensive realistic simulations demonstrate that CASRA significantly outperforms state-of-the-art baselines across all key metrics, achieving 66.7% higher semantic fidelity (0.897), 35.8% lower emergency latency (12.14 ms), and 31.8% higher resource efficiency through a convex optimization model with dynamic weighting. This model demonstrates excellent dynamics across a broad range of operation scenarios in vehicles, as well as being computationally efficient (0.15 ms execution time). The strong performance across various scenarios, statistical significance, and energy and spectrum efficiency makes CASRA an attractive solution. It facilitates dependable and intelligent vehicular communication for real-time 6G networks. Moreover, the findings provide CASRA as a significant step forward in the direction of facilitating trustworthy, effective, and intelligent transportation ecosystems in which semantic awareness and physical-layer optimization are seamlessly unified.

Future research will examine integration with physical-layer security mechanisms and multi-agent collaborative perception. We also plan to extend CASRA to multi-cell deployments and cooperative platooning with extreme mobility, enhancing trustworthiness and scalability in more complex vehicular environments.

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TABLE VI
COMPUTATIONAL COMPLEXITY AND FEASIBILITY ANALYSIS

Method	Theoretical Complexity	Avg. Exec. Time (ms)	Scalability Index	Key Limitation
Proposed CASRA	$O(N \log N)$	0.15 ± 0.02	0.74	Requires context parameter estimation
Channel-Aware	$O(N)$	0.07 ± 0.01	0.91	Ignores semantic meaning
SA_VA-ISAC	$O(N^2)$	0.10 ± 0.02	0.73	Static semantic weights
NOMA-Based	$O(N \log N)$	0.11 ± 0.02	0.79	Poor fairness, complex interference management

TABLE VII
ABLATION STUDY: IMPACT OF DISABLING INDIVIDUAL WEIGHT COMPONENTS

Variant	Disabled Component	Semantic Fidelity
Full CASRA	—	0.897
No Semantic	Ψ_{sem}	0.721
No Temporal	Ψ_{temp}	0.768
No Context	Ψ_{ctx}	0.792
No Channel	Ψ_{chan}	0.815

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