Smart Environments and Integrated Sensing and Communication: Opportunities and Challenges from Link Design to Network Cooperation

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Abstract

Smart environments and integrated sensing and communication are becoming key evolutionary directions for 6G wireless systems to move from "signal transmission" toward "environment-cooperative sensing and active control." Unlike the traditional design paradigm that regards the environment as an external random condition, smart environments transform propagation paths, array geometry, coverage topology, and multi-node cooperation modes into optimizable system degrees of freedom through programmable metasurfaces, intelligent reflecting and transmitting surfaces, vehicle-mounted surfaces, unmanned aerial vehicles and other autonomous platforms, reconfigurable antennas, and multi-base-station cooperative networks. Integrated sensing and communication, by sharing waveforms, spectrum, and infrastructure, provides real-time feedback for smart environment control in terms of environment understanding, target localization, blockage sensing, and state prediction, thereby forming a closed-loop system in which "the environment empowers sensing and communication, and sensing and communication feed back to the environment." This paper systematically reviews the conceptual boundaries, core technologies, typical architectures, key gain mechanisms, and network-level cooperation modes of smart environments and integrated sensing and communication, with a focus on the roles of fixed deployed surfaces, vehicle-mounted surfaces, hybrid sensing surfaces, unmanned aerial vehicle platforms, fluid antennas, and multi-base-station cooperative communication and sensing networks in coverage extension, channel-rank reshaping, enhancement of target resolvability, multistatic sensing, and sensing-assisted communication. Furthermore, it summarizes the common design issues in this field regarding performance metrics, optimization variables, and system closed loops, and analyzes the design conflicts between the demand for high-rank channels and the preference for line-of-sight links, as well as between the demand for communication decorrelation and the demand for sensing geometric diversity. In conjunction with typical application scenarios such as the Internet of Vehicles, industrial manufacturing, indoor spaces, and space-air-ground integrated networks, this paper summarizes the main challenges in current research and identifies research directions worthy of further in-depth investigation.

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Smart Environments and Integrated Sensing and Communication: Opportunities and Challenges from Link Design to Network Cooperation

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Abstract Integrated smart environments and communication sensing are becoming a key evolutionary direction for 6G wireless systems, shifting from "signal transmission" toward "environment-cooperative sensing and active control." Unlike traditional design approaches that regard the environment as an external random condition, smart environments use programmable metasurfaces, intelligent reflecting surfaces, vehicle-mounted surfaces, unmanned aerial vehicles and other autonomous platforms, reconfigurable antennas, and multi-base-station cooperative networks to transform propagation paths, array geometry, coverage topology, and multi-node collaboration modes into optimizable system degrees of freedom. Integrated communication and sensing, meanwhile, provides real-time feedback for smart-environment control through the sharing of waveforms, spectra, and infrastructure in environmental understanding, target localization, blockage sensing, and state prediction, thereby forming a closed-loop system of "environment-empowered communication and communication-feedback environment sensing."This paper systematically reviews the conceptual boundaries, core technologies, typical system architectures, key enhancement mechanisms, and network-level cooperation modes of integrated smart environments and communication sensing, with emphasis on the roles of fixed deployed surfaces, vehicle-mounted surfaces, hybrid sensing surfaces, unmanned aerial vehicle platforms, fluid antennas, and multi-base-station cooperative communication-and-sensing networks in coverage expansion, channel rank reshaping, enhanced target resolvability, multi-base-station sensing, and sensing-assisted communication. Furthermore, the paper summarizes common design issues in this field in terms of performance metrics, optimization variables, and system closed loops, and analyzes design conflicts among high-speed-rail channel requirements and line-of-sight link preferences, communication decorrelation requirements and sensing geometry diversity requirements. In conjunction with typical application scenarios such as the Internet of Vehicles, industrial manufacturing, indoor spaces, and space–air–ground integrated networks, it summarizes the main difficulties

Figure diagram: coupling relationship between smart environments and ISAC. The diagram shows "Smart environment" on the left, "ISAC networks" on the right, "Interplay" between them, "Enhance environment engineering efficiency" above, and "Performance improvement based on channel control" below.

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Keywords smart environment, integrated sensing and communication, reconfigurable intelligent surface, intelligent propagation engineering, cooperative sensing network, reconfigurable antenna

1 Introduction

For 6G application scenarios such as intelligent transportation, industrial automation, low-altitude networks, and immersive interaction, wireless networks not only need to transmit information at high speed and reliably, but also must continuously acquire the positions, motion, and structural states of users, targets, and the surrounding environment, so as to support beam management, mobility management, environmental interaction, and autonomous decision-making. At the same time, large bandwidths, high carrier frequencies, large-scale arrays, and dense network deployments not only enhance communication capability, but also provide a physical foundation for high-resolution time-delay, Doppler, and angle measurements [$1 \sim 3$]. If communication and sensing continue to adopt mutually independent spectrum, hardware, and network facilities,

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Figure 1 Coupling relationship between smart environments and ISAC.

This will further intensify spectrum competition, repeated deployment, and energy-consumption overheads. Therefore, integrated sensing and communication (ISAC) is widely regarded as one of the important candidate capabilities for sixth-generation mobile communication networks (sixth-generation, 6G). Its basic idea is to complete information transmission and environmental sensing tasks simultaneously under the same set of wireless infrastructure, spectrum resources, and signal-design framework. This not only improves the utilization efficiency of spectrum, hardware, and energy, but can also use sensing results to assist beam tracking, resource scheduling, and network control, enabling future wireless networks to possess native capabilities for location sensing, target detection, trajectory tracking, environmental reconstruction, and situation understanding[^4]. However, most traditional ISAC studies assume that the signal propagation environment is predetermined and uncontrollable, and system design is concentrated on link-level variables such as waveform, beam, power, time-frequency resources, and receiver processing[^5,^6]. This assumption has obvious limitations in dynamic scenarios such as mobile broadband, Internet of Vehicles, industrial Internet of Things, and space–air–ground integrated networks. These limitations are mainly reflected in aspects such as the susceptibility of high-frequency propagation to blockage, severe sensing echo path loss, inconsistent channel-structure requirements for multi-user communication and multi-target sensing, and often insufficient coverage and geometric diversity from a single-station perspective.

At the same time, active shaping technologies for the signal propagation environment itself are developing rapidly. Typical representatives include smart metasurface technologies such as reconfigurable intelligent surface (RIS/intelligent reflecting surface, IRS), simultaneously transmitting and reflecting RIS (STAR-RIS/intelligent omni-surface, IOS), and stacked metasurfaces; mobile/relay nodes such as unmanned aerial vehicle (UAV), high-altitude platforms (HAPs), and low-orbit satellites; as well as intelligent antenna technologies such as fluid antenna (FA), movable antenna (MA), rotatable antenna (RA), and pinching antenna (PA)[^7-^12]. Together, these technologies point to a broader concept: the "smart environment," meaning that wireless systems no longer merely adapt to the environment, but can, to a certain extent, reconstruct, compensate for, and even cooperatively utilize the environment in order to create more favorable propagation, sensing, and computing conditions. It should be noted that the "smart environment" referred to in this article is not synonymous with artificial intelligence; rather, it is a systematic generalization of a class of environment-enhancing wireless technologies. Here, "smart" mainly means that the propagation environment can be transformed from passive, random, and uncontrollable external conditions into observable and configurable system components that can be dynamically adjusted according to communication and sensing feedback. Accordingly, the research object of ISAC is further expanded from "jointly designing communication and sensing" to "jointly designing communication, sensing, and the propagation environment."

From the perspective of this new joint design, the relationship between smart environments and ISAC is not a simple superposition, but rather a deep bidirectional coupling, as shown in Figure 1. On the one hand, by adding virtual line-of-sight links, regulating path loss, changing channel correlation and rank structure, and improving the observability of target geometry, smart environments provide new degrees of freedom (degree of freedom, DoF) for ISAC system design, thereby expanding coverage and improving communication and

Figure 2. Schematic of smart environment and ISAC.

Figure 2: Figure 2. Schematic of smart environment and ISAC.

sensing performance[^7-^11]. On the other hand, by continuously acquiring state information about users, targets, blockers, and scatterers, ISAC provides low-overhead, real-time, and task-related feedback for environmental control, enabling RIS phase control, UAV trajectory design, antenna-position reconfiguration, and multi-base-station coordination to overcome high-overhead methods that purely rely on full-dimensional channel state information (channel state information, CSI) estimation[^10,^11,^13]. Therefore, the relationship between smart environments and ISAC should be understood more accurately as follows: smart environments transform propagation space from "given parameters" into "controllable resources," while ISAC provides closed-loop sensing and prediction capabilities for the control of such resources.

Figure 2 Schematic of smart environment and ISAC.

Existing related work has revealed the above trends from different perspectives

[14], 15

. As shown in Figure 2, RIS-enhanced ISAC research has evolved from the initial expansion of coverage and beam-gain enhancement

[16]–18

to multi-target resolution, innovation in sensing architectures, target load surfaces, mutualistic cooperation, and network-level joint optimization

[7]–9, 19–24

; work oriented toward broader intelligent propagation engineering has begun to incorporate richer environmental-control means such as fluid antennas, UAVs, and near-field propagation

[10], 25

; and network-level ISAC research has further incorporated multi-base-station cooperation, multi-site sensing, task/data/signal-level collaboration, and stochastic-geometry analysis into a unified framework

[11], 13

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The emphases of existing survey research can mainly be grouped into three categories, although the categories are not completely independent of one another. The first category focuses mainly on RIS- or intelligent-surface-assisted ISAC, systematically discussing surface architectures, beam design, target detection, and parameter estimation [26–29]. The second category extends the scope to UAVs, mobile platforms, reconfigurable antennas, and intelligent propagation engineering, with emphasis on analyzing the collaborative relationships between different environmental-control technologies and ISAC [30, 31]. The third category focuses on cooperative, distributed, or cell-free ISAC, mainly discussing network architecture, synchronization, signaling, interference management, and multi-site sensing [32–34]. Table 1 provides a concrete comparison of representative works in these categories. As can be seen from Table 1, existing surveys are highly targeted within their respective topics. The distinction of this paper does not lie in making a further classification of a particular type of device, but rather in establishing a unified analytical framework that runs through the link, local-system, and network levels. Specifically, this paper regards intelligent surfaces, mobile platforms, reconfigurable antennas, and multi-base-station cooperation as different implementations of degrees of freedom in propagation paths, spatial geometry, array structures, and network collaboration, respectively, and discusses, under a unified model, their joint impacts on channel gain, rank structure, observation geometry, and network performance. On this basis, with "environment-empowered communications and sensing–sensing/communication-information-driven environmental control" as the main thread, this paper further incorporates multi-time-scale control, low-dimensional state driving, radio environment maps, digital twins, and task-oriented metrics into a closed-loop design framework.

Based on the above, this paper provides a systematic review of the key issues in the integration of smart environments with integrated communication and sensing. The main contributions of this paper are reflected in three aspects: first, it presents a unified conceptual framework for smart environments and ISAC, clarifying that the core of this direction is not the gain of a single device, but the incorporation of propagation, topology, and cooperation relationships into a programmable closed loop; second, it summarizes the common issues in this field from the three levels of system structure, mechanisms, and optimization, highlighting the fact that the environmental-control objectives of communication and sensing are not always aligned; third, on the basis of existing work, it further proposes directions worthy of in-depth development, such as multi-time-scale environmental control, task-oriented metrics, AI-native closed loops, and wireless digital twins.

2 Conceptual Reconstruction of Smart Environments and Integrated Communication and Sensing

To avoid narrowly equating the "smart environment" with RIS, or confusing it with artificial intelligence (AI), this paper first clarifies its conceptual boundaries. The smart environment referred to in this paper is a systematic abstraction of environment-enhanced wireless technologies, and its "intelligence" is mainly manifested in three aspects:

Table 1 Comparison of This Survey with Existing Related Surveys

Existing works	RIS/IRS	UAV	Reconfigurable antennas	Multi-BS/network coordination	ISAC-driven closed-loop environment control	Unified cross-tech models & metrics	Multi-timescale control	Hierarchical link-to-network organization
[26]		–	–	–		–	–	–
[27]				–			–	–
[28]		–	–	–			–	–
[29]		–	–				–	
[30]								
[31]			–				–	
[32]							–	
[33]	–		–		–		–	
[34]							–	
Our								

Note: denotes a primary research focus with systematic discussion; indicates partial coverage but not as a main organizing theme; "–" indicates no substantive discussion. The comparisons reflect the scope and organizational perspective of each survey, not the depth of treatment in the respective topics.

First is observability, meaning that the system can obtain propagation states, user states, and target states through communication and sensing signals; second is reconfigurability, meaning that the system can, with the aid of intelligent metasurfaces, mobile platforms, reconfigurable antennas, and multi-node collaboration, proactively change propagation paths, array geometry, and network topology; third is closed-loop adaptability, meaning that the system can continuously adjust environmental control variables according to observation results. AI can be used for state prediction and control-strategy solving, but it is not a necessary condition for constituting an intelligent environment. Based on the above understanding, this paper defines an intelligent environment as a general term for systems that use various reconfigurable propagation, movable topology, and variable-array technologies to actively shape the electromagnetic propagation process across multiple dimensions—such as time, frequency, space, and geometric topology—so as to more efficiently support communication, sensing, and related computing tasks. Compared with traditional wireless networks, intelligent environments add at least three types of controllable degrees of freedom. First, path freedom, namely creating or strengthening effective propagation paths that originally do not exist or are weak through reflection, refraction, diffraction, near-field focusing, and curved-wave beams. Second, geometric freedom, namely reconfiguring the relative geometric relationships among the transmitter, receiver, and target by changing surface positions, platform trajectories, array shapes, and antenna port locations. Third, collaboration freedom, namely organizing originally isolated local observation and transmission processes into a larger-scale collaborative system through multi-node joint scheduling and multi-site cooperation.

On this basis, the coupling between intelligent environments and ISAC can be divided into three progressively deepening levels. As shown in Fig. 3, the first level is "coexistence enhancement," in which the intelligent environment is regarded as an additional channel-gain device used to alleviate blockage, enhance coverage, and improve the link budget. This level focuses on surface gain, reflection gain, path gain, and range compensation. The second level is "joint design," in which, given environmental devices, beamforming, phase, time allocation, power control, and trajectory design are jointly optimized, so that communication and sensing achieve better performance tradeoffs under unified constraints. The third level is "closed-loop mutual benefit," in which sensing results are explicitly used for environmental control, and environmental control further shapes the subsequent sensing and communication conditions, thereby forming a dynamic closed loop. The discussions in the literature [8-10] on sensing-assisted communication, communication-assisted sensing, and communication–sensing mutual benefit correspond precisely to the core idea of this level.

From the perspective of system modeling, traditional ISAC mostly focuses on resource reuse and performance tradeoffs brought about by a unified waveform, whereas intelligent-environment-enhanced ISAC requires additionally characterizing a "controllable propagation layer." This means that the channel model is no longer merely a static mapping between users and base stations, but should include such contents as the base-station–intelligent-metasurface–user relationship, platform mobility trajectories, operating modes of the intelligent metasurface, and the evolution of environmental states. Especially in RIS-assisted sensing scenarios, communication usually favors strong line-of-sight (LoS) and highly correlated gains, while high-quality target-parameter estimation often requires that the RIS–receiver have a richer multiple-input multiple-output (MIMO) structure and that a relatively strong LoS link be maintained between the RIS and the target [8,35]. Therefore, the objective of environmental control cannot simply be equated with "maximizing received power" ; rather, gain, correlation, rank,

Figure 3: Three levels of coupling between smart environment and ISAC: from coexistence enhancement to closed-loop reciprocity.

Figure 3: Figure 3: Three levels of coupling between smart environment and ISAC: from coexistence enhancement to closed-loop reciprocity.

identifiability, and control cost must be considered simultaneously.

Furthermore, the role of intelligent environments in ISAC needs to be analyzed systematically at the network level. For a single-site system, environmental control mainly changes the local···

Figure 3 Three levels of coupling between smart environment and ISAC: from coexistence enhancement to closed-loop reciprocity.

local propagation and local observation

[36]

; whereas in multi-base-station cooperative systems, the smart environment not only affects the effective gain of a single link, but also changes the interference structure, multi-base-station sensing geometry, user correlativity, and network-level coverage quality

[11, 13]

. Therefore, the research paradigm for smart-environment-enhanced ISAC is shifting from device-driven toward system-driven and network-driven: the former emphasizes "how many dB of gain the device can bring," while the latter pays more attention to "whether environmental control can substantially improve system observability, network schedulability, and closed-loop operating efficiency." This transition is also the main thread of the subsequent discussion in this paper.

2.1 Basic Framework and System Model

To ensure that the following discussion does not remain merely at the conceptual level, it is necessary to provide a minimal mathematical modeling framework that can simultaneously cover smart-environment technologies such as fixed RIS, STAR-RIS, vehicle-mounted surfaces, UAV platforms, and reconfigurable antennas. Unlike scenario-specific modeling, this paper emphasizes a unified abstraction: the smart environment is viewed as a "controllable propagation layer" located between the transmitter and the user (which may be a communication user or a sensing user). Its role is to jointly change the effective channels, observation geometry, and resource overhead of communication links and sensing links by controlling variables such as surface phase/amplitude, reflection-transmission splitting, platform position, and array geometry

[8–11, 13, 37–39]

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To clarify the correspondence between the unified model and subsequent specific technologies, the system' s joint control variables are further denoted as

$$\mathbf{z} = \{\mathbf{W}, \Theta, \mathbf{q}, \mathbf{p}, \mathbf{A}, \eta\}, \qquad (1)$$

where $\mathbf{W}$ denotes transmit beamforming and power-control variables, Θ denotes the phase-amplitude or transmission-reflection control variables of intelligent metasurfaces, $\mathbf{q}$ denotes the position and trajectory of mobile platforms, $\mathbf{p}$ denotes the position or port state of reconfigurable antennas, $\mathbf{A}$ denotes node association and cooperative clustering variables, and η denotes the time or energy allocation ratio among communication, sensing, and control resources. Therefore, the feasible domain in a general optimization problem can be further decomposed as

$$\Theta \in \mathcal{C}_{\text{surf}}, \quad \mathbf{q} \in \mathcal{C}_{\text{mob}}, \quad \mathbf{p} \in \mathcal{C}_{\text{ant}}, \quad \mathbf{A} \in \mathcal{C}_{\text{net}}, \qquad (2)$$

corresponding respectively to surface passivity or transmission-energy constraints, platform-motion and energy-consumption constraints, antenna movement-region and minimum-distance constraints, as well as node association, cooperative-cluster size, and backhaul-capacity constraints. The modeling of the various technologies discussed later can all be understood as concrete instantiations of the above variable subsets and their feasible domains.

2.1.1 Signal Transmission/Reception Model

(1) Unified transmit-signal model:

$$\mathbf{x}(t) = \sum_{k=1}^{K} \mathbf{w}_k s_k(t), \quad \mathbb{E}\{|s_k(t)|^2\} = 1, \qquad (3)$$

Here, K denotes the total number of waveforms, $s_k(t)$ may represent baseband waveforms for different users, different tasks, or different beam directions, and $\mathbf{w}_k$ corresponds to the transmit beam shared or partially shared by communication and sensing. This expression preserves the most essential unity of ISAC: the same set of transmit degrees of freedom can carry information transmission and also provide known reference templates for subsequent parameter estimation [$1 \sim 3$].

(2) RIS/IRS-assisted received-signal model:

$$y_k(t) = \left(\mathbf{h}_{d,k}^H + \mathbf{h}_{r,k}^H \Theta \mathbf{G}\right) \mathbf{x}(t) + n_k(t), \qquad (4)$$

where $\mathbf{G}$ denotes the channel from the base station to the environmental layer, $\mathbf{h}_{r,k}$ denotes the cascaded outgoing channel from the environmental layer to user k, and $\mathbf{h}_{d,k}$ denotes a possible direct link. For a fixed-deployment RIS, Θ is the commonly used reflection-control matrix; for STAR-RIS, transmission and reflection control matrices should be introduced separately.

(3) Unified echo-signal model.

Unlike the one-way propagation of communication links, sensing echoes need to further distinguish the forward propagation from the transmitter to the target, target scattering, and the return propagation from the target to the receiver. The corresponding unified echo model can be written as

$$\mathbf{y}_{\mathrm{s}}(t) = \sum_{q=1}^{Q} \mathbf{G}_{q\mathrm{R}}(\Theta_{\mathrm{R}})\mathbf{S}_q\mathbf{G}_{\mathrm{T}q}(\Theta_{\mathrm{T}})\mathbf{x}(t-\tau_q)e^{j2\pi\nu_q t} + \mathbf{n}_{\mathrm{s}}(t), \qquad (5)$$

where $\mathbf{G}_{\mathrm{T}q}(\Theta_{\mathrm{T}})$ denotes the forward propagation channel from the transmitter to target q, $\mathbf{S}_q$ denotes the target scattering response, and $\mathbf{G}_{q\mathrm{R}}(\Theta_{\mathrm{R}})$ denotes the return propagation channel from the target to the receiver. Both propagation channels may contain direct paths and intelligent-environment-controlled paths. τ_q and ν_q denote the corresponding time delay and Doppler frequency shift, respectively.

Here, Θ_{T} and Θ_{R} are adopted separately to distinguish the positions at which the intelligent metasurface acts in forward and return propagation; this does not imply that the two must necessarily be mutually independent control variables. For a quasi-static RIS that is reciprocal and maintains a fixed configuration within the same sensing period, usually $\Theta_{\mathrm{T}} = \Theta_{\mathrm{R}} = \Theta$; only in time-varying surfaces or time-division reconfiguration scenarios may the two adopt different configurations.

For a far-field point target, $\mathbf{S}_q$ can be further reduced to a rank-one response characterized by the target scattering coefficient, and the corresponding equivalent two-way channel can be expressed as

$$\mathbf{H}_q^{2\mathrm{w}} = \alpha_q\sqrt{\beta_{\mathrm{T}q}\beta_{q\mathrm{R}}}\mathbf{a}_{\mathrm{R}}(\vartheta_{q\mathrm{R}})\mathbf{a}_{\mathrm{T}}^H(\vartheta_{\mathrm{T}q}), \qquad (6)$$

where α_q is the target scattering coefficient, $\beta_{\mathrm{T}q}$ and $\beta_{q\mathrm{R}}$ denote the power gains of forward and return propagation, respectively, and $\mathbf{a}_{\mathrm{T}}(\cdot)$ and $\mathbf{a}_{\mathrm{R}}(\cdot)$ denote the transmit and receive array responses, respectively. This model may be further degraded into a monostatic or bistatic sensing model depending on whether the transceiver is co-located.

2.1.2 Signal-Propagation Control Variables

(1) Basic RIS/IRS control variables:

$$\Theta = \mathrm{diag}(\rho_1 e^{j\theta_1}, \dots, \rho_L e^{j\theta_L}), \quad 0 \le \rho_l \le 1, \quad \theta_l \in [0, 2\pi), \tag{7}$$

where ρ_l and θ_l denote the amplitude and phase control of the l-th element, respectively. When a purely passive RIS is used, usually $\rho_l \approx 1$, while more general reconfigurable surfaces, hybrid RISs, or active elements allow joint amplitude–phase adjustment.

(2) STAR-RIS/IOS control variables. For STAR-RIS/IOS and vehicular intelligent transmissive–reflective surfaces, it is necessary to further characterize the energy splitting and independent phase control of the transmission and reflection links, as follows:

$$\Theta^{\mathrm{t}} = \mathrm{diag}\left(\sqrt{\beta_\ell^{\mathrm{t}}} e^{j\theta_\ell^{\mathrm{t}}}\right)_{\ell=1}^{L}, \quad \Theta^{\mathrm{r}} = \mathrm{diag}\left(\sqrt{\beta_\ell^{\mathrm{r}}} e^{j\theta_\ell^{\mathrm{r}}}\right)_{\ell=1}^{L}, \tag{8}$$

where β_ℓ^{t} and β_ℓ^{r} are the transmission and reflection power allocation coefficients of the ℓ-th element, respectively, while $\sqrt{\beta_\ell^{\mathrm{t}}}$ and $\sqrt{\beta_\ell^{\mathrm{r}}}$ are the corresponding amplitude coefficients. For an ideal lossless energy-splitting mode, they satisfy

$$\beta_\ell^{\mathrm{t}} + \beta_\ell^{\mathrm{r}} = 1, \quad 0 \le \beta_\ell^{\mathrm{t}}, \beta_\ell^{\mathrm{r}} \le 1. \tag{9}$$

Considering device losses, the above inequality should accordingly be relaxed to $\beta_\ell^t + \beta_\ell^r \le 1$.

For mode switching, the power states of each element satisfy $\beta_\ell^t, \beta_\ell^r \in \{0, 1\}$ and their sum is 1; for time switching, transmission and reflection operate in different time intervals, respectively, and are described by the time-slot proportions. Equation (8) adopts an ideal amplitude–phase control model; for practical passive STAR-RIS, the transmission and reflection phases may also have to satisfy coupling constraints determined by the device structure. This model is consistent with the two-stage protocol for vehicle-network sensing-assisted communication in Ref. [9]: in the joint communication and sensing stage, some energy is reflected back to roadside units for vehicle state measurement, while the remaining energy is transmitted to in-vehicle terminals for data transmission; in the subsequent pure communication stage, more degrees of freedom can be shifted to the communication side[1].

(3) Mobile-platform control variables. If the intelligent environment contains mobile platforms such as UAVs and HAPs, the following position-state variables also need to be introduced[2]:

$$\mathbf{q}[n+1] = \mathbf{q}[n] + \mathbf{v}[n]\Delta T, \quad \|\mathbf{v}[n]\| \le V_{\max}, \tag{10}$$

[1] 9
[2] 40

where $\mathbf{q}[n]$ denotes the position or trajectory state of the mobile platform, $\mathbf{v}[n]$ denotes the platform' s moving velocity, ΔT denotes the time-slot length, n is the time-slot index, and $V_{\max}$ denotes the maximum moving speed.

(4) Reconfigurable-antenna control variables. For new reconfigurable arrays such as fluid antennas and movable antennas, the core modeling feature is that the physical positions or equivalent radiation positions of antenna elements constitute optimizable system degrees of freedom, thereby introducing the new control dimension of array geometry in addition to traditional beamforming. Specifically, the position of the m-th antenna element is denoted by $\mathbf{p}_m \in \mathcal{P}_m$, where $\mathcal{P}_m$ is the feasible movable region of the m-th element in space. At this point, the field-response vector of the m-th antenna element at the transmitter or receiver can be expressed as:

$$(\mathbf{q}_m) = \left[e^{j\frac{2\pi}{\lambda}\rho^1(\mathbf{q}_m)}, e^{j\frac{2\pi}{\lambda}\rho^2(\mathbf{q}_m)}, \dots, e^{j\frac{2\pi}{\lambda}\rho^L(\mathbf{q}_m)}\right]^{\mathrm{T}}, \qquad (11)$$

where L denotes the number of paths, λ denotes the wavelength, $\rho^l(\mathbf{q}_m) = x_m \sin\phi_l \cos\psi_l + y_m \cos\phi_m$ is the difference between the signal propagation distance of the l-th path of the m-th antenna element and the signal propagation distance to the origin of the antenna array, where x_m and y_m denote the position coordinates of the m-th antenna element, and ϕ_l and ψ_l denote the elevation angle and azimuth angle corresponding to the arrival angle of the l-th path signal[3]. It can be seen that the response vector explicitly depends on the position set of the antenna elements, and it is precisely this dependence that endows reconfigurable antennas with unique channel-shaping capability. By optimizing $\mathbf{p}_m$, the equivalent aperture size of the array, inter-element spacing, and geometric shape can be dynamically changed, thereby regulating the spatial correlation structure of the channel, the far-field/near-field boundary, and wavefront-curvature matching characteristics. Compared with merely optimizing the surface phase, such variables directly change the line-of-sight relationship, distance path loss, observation angle, and array aperture; therefore, they have irreplaceable value in coverage extension, blockage avoidance, near-field focusing, and sensing-geometry enhancement[4].

The above formulas do not aim to construct a complete physical model applicable to all scenarios; rather, they provide a set of commonly used modeling building blocks: unified transmitted signals, communication composite channels, sensing-echo generation, surface amplitude–phase control, transmission/reflection ratio allocation, and platform or array geometric control. Subsequent discussions, whether concerning RIS/IRS, STAR-RIS/IOS, UAV mobile platforms, or reconfigurable antennas, can in essence be summarized as the combinatorial optimization of these variables under different scenarios.

[3] 41
[4] 10,37-39

2.2 Representative Performance Metrics and Optimization Problems

Intelligent-environment-enhanced ISAC covers different objectives such as detection, estimation, tracking, and task decision-making. Applicable evaluation metrics depend on the signal regime, network architecture, and specific application, and are difficult to exhaust with a fixed set of metrics. To highlight the roles of controllable propagation, array geometry, and multi-node collaboration in system performance, this paper selects several representative metrics that are commonly used in the existing literature and that can reflect the progressive relationship across the "link/system—network" hierarchy for explanation. At the link/system level, the focus is on the communication signal-to-interference-plus-noise ratio (SINR) and achievable rate, the sensing signal-to-noise ratio, and the Cramér–Rao lower bound (CRLB); at the network level, the focus is on communication/sensing area spectral efficiency, regional CRLB, and coverage probability. The above metrics are intended to provide exemplary measures for unified modeling and optimization-problem design, and do not constitute a complete set of metrics. For specific tasks, metrics such as bit error rate, detection probability and false-alarm probability, minimum mean-square error, tracking error, delay, energy efficiency, and task success probability may also be used. It should be pointed out that these metrics are not mutually isolated: once environmental control variables change, communication SINR, echo quality, Fisher information, and control overhead often change synchronously; hence, their interactions need to be analyzed under an integrated framework[5].

2.2.1 Link-/System-Level Performance Metrics

(1) Communication SINR. Based on the unified model representation, the basic communication performance metric can be expressed as

$$\gamma_k = \frac{\left|\left(\mathbf{h}_{d,k}^H + \mathbf{h}_{r,k}^H \Theta \mathbf{G}\right)\mathbf{w}_k\right|^2}{\sum_{j\neq k}\left|\left(\mathbf{h}_{d,k}^H + \mathbf{h}_{r,k}^H \Theta \mathbf{G}\right)\mathbf{w}_j\right|^2 + \sigma_k^2}, \tag{12}$$

and the corresponding achievable rate is usually written as $R_k = \log_2(1+\gamma_k)$. In intelligent-environment scenarios, θ, $\mathbf{q}[n]$, and $\mathbf{p}[n]$ not only change the desired signal power, but also alter the multiuser interference structure. Therefore, simply understanding "environment control" as "link-level preprocessing" is not entirely accurate; more precisely, it reshapes the entire multiuser channel matrix.

(2) Sensing signal-to-noise ratio. On the sensing side, the most basic link processing usually begins with matched filtering or delay–Doppler processing [42], as shown below:

[5] 1,8,10,11,13

$$\Lambda_q(\tau,\nu) = \int a_r^H(\theta_q)\mathbf{y}_r(t)s^*(t-\tau)e^{-j2\pi\nu t}\,dt. \qquad (13)$$

For orthogonal frequency division multiplexing (OFDM) or pulse-based systems, this step is equivalent to projecting the received signal onto the transmitted reference waveform, thereby forming a peak structure in the delay and Doppler dimensions. Around this output, one can further stack angular-domain beamforming, multiple signal classification (MUSIC)/estimation of signal parameters via rotational invariance techniques (ESPRIT) super-resolution processing, or perform noncoherent/coherent fusion in multistatic scenarios [1, 8, 11].

Writing the matched-filter output corresponding to target q as $\Lambda_q = \Lambda_q^{\mathrm{sig}} + \Lambda_q^{\mathrm{in}}$, where Λ_q^{sig} denotes the target-signal component and Λ_q^{in} denotes the undesired component formed by other targets, clutter, interference, and noise, the corresponding sensing-output SINR is defined as

$$\gamma_q^{\mathrm{sen}} = \frac{\mathbb{E}\left[\left|\Lambda_q^{\mathrm{sig}}(\tau_q,\nu_q)\right|^2\right]}{\mathbb{E}\left[\left|\Lambda_q^{\mathrm{in}}(\tau_q,\nu_q)\right|^2\right]}, \qquad (14)$$

where the expectation can be averaged according to a specific model over communication data, noise, interference, and random scattering parameters. Since this definition is based on second-order power, even if the target scattering coefficient is a zero-mean random variable, it can still correctly reflect nonzero echo energy. When Λ_q^{in} contains only noise, this metric correspondingly degenerates into the sensing SNR. Although it is more abstract than the detection probability and false-alarm probability, it facilitates analysis of the influence of environmental control, array aperture, and surface deployment on echo-peak quality [43]. For the many sensing-assisted communication cases shown in review papers, an increase in echo SINR implies more robust state estimation, which can further reduce subsequent communication beam-training overhead [9, 10].

(3) Cramér-Rao bound. When the task objective is upgraded from "detecting a target" to "high-accuracy estimation of target parameters," the Fisher information matrix (FIM) and the Cramér-Rao bound become more fundamental performance metrics [44], as shown below:

$$\mathbf{J}_{ij}(\eta) = \frac{2}{\sigma_r^2}\Re\left\{\frac{\partial\mu^H}{\partial\eta_i}\frac{\partial\mu}{\partial\eta_j}\right\}, \qquad \mathrm{CRLB}(\eta_i) = [\mathbf{J}^{-1}]_{ii}, \qquad (15)$$

where $\mathbf{J}_{ij}(\eta)$ denotes the FIM of parameter η_i and parameter η_j, μ denotes the observation information, and η denotes the parameter vector to be sensed. Under regularity conditions, if the Fisher information matrix $\mathbf{J}(\eta)$ is nonsingular, then any unbiased estimator $\hat{\eta}$ satisfies

$$\mathrm{Cov}(\hat{\eta}) \succeq \mathbf{J}^{-1}(\eta), \qquad \mathrm{var}(\hat{\eta}_i) \geq [\mathbf{J}^{-1}(\eta)]_{ii}. \qquad (16)$$

Therefore, the CRLB is the theoretical lower bound on the covariance or variance of unbiased estimation errors. If the Fisher information matrix degenerates in a certain parameter direction, then a finite CRLB cannot be obtained in that direction. The reason RIS-enhanced sensing repeatedly emphasizes high-rank channels, observation geometry, and surface deployment locations is precisely that these factors directly affect the sensitivity of the Fisher matrix to the parameter η, thereby changing the attainable error lower bound [8, 11, 22].

In addition, in dynamic scenarios, instantaneous estimation alone is insufficient; it is usually also necessary to combine a state-space model for tracking. A typical state evolution model can be expressed as

$$\mathbf{u}_n = \mathbf{F}\mathbf{u}_{n-1} + \mathbf{w}_n, \qquad \mathbf{z}_n = \mathbf{h}(\mathbf{u}_n) + \mathbf{v}_n, \qquad (17)$$

where $\mathbf{u}_n$ denotes the user state, $\mathbf{F}$ denotes the state-evolution matrix, $\mathbf{h}$ denotes the measurement model, and $\mathbf{w}_n$ and $\mathbf{v}_n$ denote the process noise and measurement noise, respectively. Through methods such as the extended Kalman filter, unscented Kalman filter, or particle filter, this model can combine the current echo measurement with the state prediction from the previous time slot. The two-stage protocol for vehicular networks in [9] essentially uses this closed-loop mechanism of "measurement-prediction-reconfiguration" to convert sensing results into communication gains[^9].

2.2.2 Network-Level Performance Metrics

For network-level systems, metrics such as area spectral efficiency (ASE), CRLB coverage probability, and unit-energy comprehensive efficiency can be further introduced[^11,^13,^45,^46]. Network energy efficiency, task-completion latency, and collaborative backhaul overhead are likewise of great significance, but their specific definitions are usually related to the application scenario and system boundaries, and therefore are not expanded upon here.

(1) Communication/sensing ASE. To better describe the performance of an ISAC network, [13] proposes a unified area spectral efficiency to characterize the average communication/sensing performance of an ISAC network, as follows:

$$T_c^{\mathrm{ASE}} = \lambda_b K R_c, \qquad T_s^{\mathrm{ASE}} = \lambda_b J R_s, \qquad (18)$$

where λ_b denotes the intensity of the Poisson point process (PPP) of base stations in the region, K denotes the number of users, J denotes the number of targets, R_c denotes the average unit transmission rate of users, and R_s denotes the average radar information rate of targets.

(2) Area CRLB. To evaluate the overall localization performance over the entire region of interest, [47] defines the area CRLB (A-CRLB):

$$\overline{\text{CRLB}} = \frac{1}{|\mathcal{A}|}\int_{\mathbf{t}\in\mathcal{A}} \text{CRLB}(\mathbf{t})d\mathbf{t}, \qquad (19)$$

where $|\mathcal{A}|$ denotes the size (length/area/volume) of the sensing region $\mathcal{A}$, and $\text{CRLB}(\mathbf{t})$ denotes the theoretical lower bound of the parameter-estimation error when the target is located at the random position $\mathbf{t}$.

(3) Communication/sensing coverage probability. In addition to average rate and average localization error, network-level ISAC also needs to characterize whether random users or random targets can meet basic quality-of-service requirements. Therefore, the communication coverage probability and sensing coverage probability can be defined respectively as

$$P_{\text{cov}}^{c}(\gamma_{\text{th}}) = \Pr\{\gamma_c(\mathbf{u}) \geq \gamma_{\text{th}}\}, \qquad (20)$$

$$P_{\text{cov}}^{s}(\epsilon_{\text{th}}) = \Pr\{\text{CRLB}(\mathbf{t}) \leq \epsilon_{\text{th}}\}, \qquad (21)$$

where $\gamma_c(\mathbf{u})$ denotes the communication SINR of a user at the random position $\mathbf{u}$, and γ_{th} is the SINR threshold required for reliable communication service; $\text{CRLB}(\mathbf{t})$ denotes the theoretical lower bound of the target-parameter error at the random position $\mathbf{t}$, and ϵ_{th} is the sensing-accuracy threshold. $P_{\text{cov}}^{c}(\gamma_{\text{th}})$ measures the probability that a user obtains reliable communication service; correspondingly, the sensing coverage probability $P_{\text{cov}}^{s}(\epsilon_{\text{th}})$ denotes the probability that the theoretical error lower bound at a random target position does not exceed a given threshold. This metric is used to characterize the potential sensing capability of the network, but it is not directly equal to the probability that the actual error of a specific estimator satisfies this threshold. Furthermore, if both communication and sensing are required to satisfy service conditions simultaneously, the joint communication-and-sensing coverage probability can be defined as

$$P_{\text{cov}}^{\text{ISAC}} = \Pr\{\gamma_c(\mathbf{u}) \geq \gamma_{\text{th}}, \text{CRLB}(\mathbf{t}) \leq \epsilon_{\text{th}}\}, \qquad (22)$$

This metric can reflect the network’s joint guarantee capability between communication services and sensing services, and is particularly suitable for evaluating the impact of strategies such as multi-base-station collaboration, RIS deployment, UAV-assisted coverage, and intelligent environmental control on overall service continuity.

2.2.3 Problem Design

The optimization objective of intelligent-environment-enhanced ISAC depends on the specific task and system architecture. For communication-priority scenarios, the optimization may focus on rate, SINR, or reliability; for sensing-priority scenarios, the optimization may focus on detection probability, sensing SNR, or parameter-estimation accuracy; when communication, sensing, and environmental ···

When environmental control must be jointly designed, it is necessary to further characterize the tradeoff relationship among the three. Therefore, below we give only one representative objective-construction method and general problem form, rather than treating it as the only model applicable to all scenarios.

(1) Optimization objective. Let $\mathbf{z}$ denote the design variables related to the specific system, and ξ denote system information such as the channel, target, and environmental states. A representative way to scalarize among communication, sensing, and control overhead is

$$U(\mathbf{z};\xi) = \lambda_c \tilde{f}_{\text{comm}}(\mathbf{z};\xi) + \lambda_s \tilde{f}_{\text{sense}}(\mathbf{z};\xi) - \lambda_o \widetilde{C}_{\text{overhead}}(\mathbf{x}), \tag{23}$$

where $\tilde{f}_{\text{comm}}$ and $\tilde{f}_{\text{sense}}$ respectively denote the normalized communication and sensing utilities, both uniformly expressed in the form "the larger the numerical value, the better the performance" ; for example, for a CRLB that needs to be minimized, its negative value or reciprocal may be used to construct the sensing utility. $\widetilde{C}_{\text{overhead}}$ denotes the normalized overhead of training, feedback, computation, and environmental updating. $\lambda_c, \lambda_s, \lambda_o \geq 0$ denote the relative weights of different design objectives. Normalization can avoid the impact caused by differences in the scale and numerical magnitude of different indicators on the definition of the weights. It should be noted that weighted utility is only one implementation of multi-objective tradeoff; according to task requirements, methods such as service thresholds, max–min criteria, or Pareto optimization may also be used to organize communication and sensing objectives.

(2) Problem modeling. Under the above notation, a representative class of optimization problems can be written as

$$\begin{aligned} \max_{\mathbf{z}\in\mathcal{X}} \quad & U(\mathbf{z};\xi) \\ \text{s.t.} \quad & f_{\text{comm}}(\mathbf{z};\xi) \succeq \Gamma_c, \\ & f_{\text{sense}}(\mathbf{z};\xi) \succeq \Gamma_s, \\ & C_{\text{overhead}}(\mathbf{z}) \leq C_{\max}, \end{aligned} \tag{24}$$

where Γ_c and Γ_s respectively denote communication and sensing service thresholds, and the corresponding indicators are likewise expressed numerically so that larger values indicate better performance; $\mathcal{X}$ denotes the feasible region composed of conditions such as power budget, surface-amplitude response, platform motion, antenna positions, resource allocation, and network association. The variable $\mathbf{z}$ may, according to the specific architecture, include one or more of beamforming, power, surface configuration, platform trajectory, antenna position, time-frequency resources, or collaboration clusters, and it is not required that all the above variables be optimized simultaneously in every scenario. By adjusting the weights and thresholds, this form can describe different designs such as communication-first, sensing-first, and joint communication-sensing tradeoffs. When ξ contains uncertainty, the objectives and constraints may correspondingly adopt average-performance, worst-case, or probabilistic-guarantee forms; for cross-time-slot problems, $\mathbf{z}$ may be extended to a sequence of control variables or a state-dependent policy.

The formulas given in this section do not attempt to cover all details of every class of architecture, but rather provide a unified mathematical support for the subsequent discussion in the full text: the basic signal model answers "how signals propagate through the environment," matched filtering and state tracking answer "how to extract states from echoes," while the joint optimization model answers "how to reuse these states for environmental control." In this sense, the core of intelligent environments and ISAC is not a certain device itself, but the closed-loop coupling among sensing, propagation, and control.

3 Key Technologies for Intelligent Environments

This section systematically introduces the main technical forms of intelligent environments from the perspectives of fixed deployed intelligent metasurfaces, vehicle-mounted and self-sensing surfaces, UAVs and other autonomous platforms, reconfigurable antennas, and multi-base-station collaborative networks, and compares their controllable degrees of freedom, performance gains, and implementation challenges. In fixed-deployment RIS scenarios, the main control variable is Θ, and the general optimization problem correspondingly adds constraints such as unit-modulus, discrete phase, amplitude limitation, or STAR-RIS transmission/reflection energy conservation. For UAVs and other autonomous platforms, the position variable $\mathbf{q}$ is mainly activated, and velocity, acceleration, flight region, collision avoidance, and energy-consumption constraints are introduced. Reconfigurable antennas correspond to position or port variables $\mathbf{p}$, whose feasible region is jointly determined by the port set, physical movement range, minimum inter-element distance, and switching speed. Multi-base-station collaboration further introduces node association and collaboration-cluster variables $\mathbf{A}$, and is subject to constraints on cluster size, backhaul capacity, synchronization accuracy, and cross-station power budget. These variables ultimately all enter the unified utility function given in Section 2.2.3 by changing the effective communication channel, sensing echo model, and control overhead.

Figure 4: Key technologies of smart environment. (a) Fixed RIS/IRS; (b) Vehicle-mounted RIS; (c) Hybrid RIS/IRS; (d) UAV mobile node; (e) reconfigurable antenna; (f) Multi-BS cooperation network

Figure 4: Figure 4: Key technologies of smart environment. (a) Fixed RIS/IRS; (b) Vehicle-mounted RIS; (c) Hybrid RIS/IRS; (d) UAV mobile node; (e) reconfigurable antenna; (f) Multi-BS cooperation network

3.1 Fixed-Deployed Intelligent Metasurfaces

Fixed-deployed RIS is still the most mature type of intelligent-environment technology in current research and has the clearest application prospects[48~50]. Its basic role is to establish a programmable virtual LoS path between the base station and users, compensate for blockage through reflection or refraction, improve link gain, and extend sensing coverage[7,8,10,51].

Figure 4 Key technologies of smart environment. (a) Fixed RIS/IRS; (b) Vehicle-mounted RIS; (c) Hybrid RIS/IRS; (d) UAV mobile node; (e) reconfigurable antenna; (f) Multi-BS cooperation network

Compared with pure communication scenarios, the key differences of RIS-assisted ISAC lie in the following: RIS must not only enhance the effective signal power, but also take into account the measurement dimension required for target-parameter estimation and the separability among targets. For example, in multi-target sensing, if multiple targets share the same RIS–receiver link, the echo directions observed at the receiver may be highly overlapping, making echo separation difficult. In this case, surface design should no longer focus only on gain, but must also reduce the correlation among different target channels, and even introduce distinguishable features for different targets through coded reflection strategies[^8].

3.2 Vehicle-Mounted and Anchor-Type Surfaces

References [8, 9] extend intelligent metasurfaces from traditional fixed infrastructure to the vehicles themselves, significantly broadening the connotation of smart-environment-enhanced ISAC. Target-mounted surfaces can actively control the echo direction, enhance the detectability of targets with small radar cross sections (radar cross section, RCS), and improve the estimation accuracy of target pose and position through multi-surface deployment. Vehicle-mounted STAR-RIS can simultaneously realize reflection and transmission on the same surface, enabling exterior roadside units to use reflected echoes for localization and tracking while also providing better data services to in-vehicle terminals through the transmitted component[^9]. The greatest feature of this type of architecture is that it transforms the "sensed target" into a "partially cooperative object," thereby breaking the assumption in traditional sensing that the target is completely passive[^52]. At the same time, however, the uncertainty of the position and orientation of target-mounted surfaces, control and feedback delay, and hardware complexity also increase significantly.

3.3 Hybrid Sensing Surfaces and Self-Sensing Surfaces

One of the greatest bottlenecks of traditional passive RIS is that the surface itself lacks observation capability, and environmental control is highly dependent on external base stations to obtain CSI or location information. To address this problem, hybrid RIS/self-sensing surface architectures embedded with a small number of sensors or active units have emerged in recent years[^8,^53]. Through the approach of "surface-local sensing + base-station fusion decision-making," such architectures improve blind-zone sensing capability and reduce global training overhead. From a system perspective, their essence is to introduce lightweight sensing and preprocessing functions inside the propagation-control device, enabling the surface to evolve from a "pure execution unit" toward an "edge observation unit." The key difficulties lie in how to make structural trade-offs among passive units, active units, and sensing units; how to allocate data-processing tasks between the surface side and the base-station side; and how to control power consumption and cost while ensuring real-time performance.

3.4 UAVs and Other Autonomous Platforms

Compared with fixed surfaces, mobile platforms such as UAVs, aerial platforms, and low-Earth-orbit satellites provide stronger geometric reconfigurability[^10,^11,^54]. They can reconstruct the viewing-distance relationship through trajectory design, expand the observation angle, compensate for ground occlusion, and, through multi-base-station or multi-platform cooperation, achieve more flexible multi-base-station sensing and cooperative coverage[^55,^56]. Such platforms are particularly suitable for air–ground integrated scenarios, sudden-coverage scenarios, and sensing tasks with high requirements for geometric diversity[^57]. However, compared with surface phase-control, platform-position reconfiguration belongs to control on a slower time scale, and is constrained by flight speed, energy consumption, payload, and safety[^58]. Therefore, in intelligent-environment-enhanced ISAC, UAVs are more suitable as medium- and slow-time-scale "topology reconstructors," rather than high-frequency rapid regulators for all scenarios.

3.5 Reconfigurable Antennas

Fluid antennas / movable antennas / pinching antennas introduce geometric degrees of freedom distinct from those of traditional fixed arrays by switching port positions within a finite space or continuously adjusting the positions of radiating elements[^10,^37,^59]. This capability has dual value in ISAC: for communications, spatial-channel fluctuations can be exploited to select more favorable ports or array shapes, thereby improving channel gain and suppressing interference; for sensing, changing the aperture and geometric distribution of the array can improve angle–distance resolution, alleviate grating-lobe problems, and enhance near-field focusing performance. Especially in millimeter-wave/terahertz and ultra-large-scale array scenarios, near-field effects are more pronounced, and antenna-position reconfiguration will directly affect wavefront-curvature matching and focus control[^60]. However, such technologies also extend the traditional problem of "fixed-array channel estimation" into one of "joint estimation and optimization of array geometry and channel," whose computational and control complexity cannot be ignored.

From a unified-model perspective, fluid antennas and movable antennas mainly correspond to antenna-position variables $\mathbf{p} = \{\mathbf{p}_m\}$. For a near-field target located at (r, θ), the array response of the m-th antenna element can be expressed as

$$a_m(r, \theta; \mathbf{p}_m) = \frac{1}{d_m(r, \theta)} \exp\left(-j\frac{2\pi}{\lambda} d_m(r, \theta)\right), \qquad (25)$$

where $d_m(r, \theta)$ denotes the distance between the target and the antenna position $\mathbf{p}_m$. Unlike a far-field fixed array, this response simultaneously contains amplitude and phase variations related to both angle and distance. Therefore, adjusting $\mathbf{p}_m$ not only changes the array aperture, but also changes the observation sensitivity corresponding to spherical-wave curvature matching and the two parameters of distance and angle.

Let the derivative matrix of the received-signal mean with respect to the target parameter $\eta = [r, \theta]^T$ be

$$\mathbf{D}(\mathbf{p}) = \left[\frac{\partial \mu}{\partial r}, \frac{\partial \mu}{\partial \theta}\right], \qquad (26)$$

then the corresponding Fisher information matrix is

$$\mathbf{J}_\eta(\mathbf{p}) = \frac{2}{\sigma^2} \Re\left\{\mathbf{D}^H(\mathbf{p})\mathbf{D}(\mathbf{p})\right\}. \qquad (27)$$

Optimizing antenna positions can reduce the correlation between the distance derivative and the angle derivative and improve the condition number of $\mathbf{J}_\eta$, thereby enhancing joint angle–distance resolution and near-field focusing performance. If ports can switch rapidly among multiple positions, observations at different instants can also form a virtual aperture; however, this gain requires the target and the dominant channel to remain approximately stable within the switching period, otherwise target Doppler and port switching will become coupled.

In multi-base-station or multi-terminal networks, reconfigurable antennas can also be used for interference shaping. Let the set of antenna positions of the b-th node be $\mathbf{P}_b$. The total interference it causes to other nodes can be summarized as

$$I(\{\mathbf{P}_b\}) = \sum_{b \neq b'} \left| \mathbf{h}_{b'}^H(\mathbf{P}_{b'}) \mathbf{w}_b(\mathbf{P}_b) \right|^2. \qquad (28)$$

By jointly selecting the antenna positions of different nodes, while maintaining the desired communication gain and sensing Fisher information, the equivalent cross-station channel correlation can be reduced, and spatial nulls can be formed in non-serving-user or non-target directions. This further expands reconfigurable antennas from a single-link port-selection tool to a network-level means for controlling interference and observation structure.

The above gains also bring implementation issues different from those of RISs and UAVs, including channel-training overhead caused by the increased number of candidate positions, port-switching or mechanical-movement delay, element coupling and feedline loss, near-field array calibration errors, and matching between position control and the channel coherence time. In multi-

In node-coordination scenarios, each node independently selecting a locally optimal position may still change the interference structure of other nodes; therefore, distributed or hierarchical position-coordination mechanisms need to be designed in conjunction with limited information exchange.

3.6 Multi-Base-Station Cooperative Networks

The ultimate value of intelligent-environment-enhanced ISAC is not limited to single-station, single-surface settings. References

$$11, 13$$

show that multi-base-station cooperation, multi-base-site sensing, coordinated multi-point (CoMP) communication, and task/data/signal-level collaboration can significantly expand sensing coverage and communication service range, and can improve interference-management capability through additional spatial degrees of freedom. From the sensing perspective, multi-base-station cooperation extends the limited observation perspective of a single station into a multi-base-site sensing architecture. The target echoes received by different base stations form complementary observation geometries in space, which not only cover blind zones that a single station cannot reach, but also significantly improve the accuracy and robustness of target-parameter estimation through the fusion of multi-view information. From the communication perspective, CoMP technology enables multiple base stations to jointly transmit to or jointly receive from the same user, thereby transforming originally harmful inter-cell interference into useful signals and improving the rate and link reliability of edge users

. However, multi-base-station cooperation is not without cost. The larger the cooperation cluster, the higher the requirements for channel-state-information sharing, backhaul-link capacity, and clock-synchronization accuracy, which are often constrained in practical deployment. Therefore, the choice of cooperation-cluster size is essentially a tradeoff between performance gain and system overhead. In addition, the optimal partitioning of communication cooperation clusters and sensing cooperation clusters is not always the same: communication cooperation tends to construct local cooperation clusters centered on users and composed of neighboring nodes in order to reduce interference, whereas sensing cooperation must consider the geometric diversity of target perspectives and the deployment principles of multiple static radars. How to jointly optimize communication and sensing cooperation clusters under a unified network architecture is one of the core problems in this direction.

3.7 Unification and Comparison of Technical Mechanisms

The physical objects regulated by different intelligent-environment technologies vary: from the electromagnetic response of surface units, to the three-dimensional position of aerial platforms, and further to the spatial geometry of antenna ports. However, if their influence on ISAC systems is abstracted to the channel-space level, they can all be understood as certain basic operations on the "communication–sensing joint channel state." This section is not limited to the specific implementation of any particular technology, but instead constructs a unified analytical framework from mathematical and geometric perspectives, in order to reveal the common laws and differentiated mechanisms by which different intelligent-environment control methods act in ISAC systems. To facilitate comparison among different intelligent-environment technologies, this paper uses "rotation," "gain adjustment," and "response reshaping" to summarize their typical dominant effects in a normalized channel space. These descriptions are intended to provide geometric intuition, rather than rigorous mathematical equivalence descriptions of actual channel transformations.

3.7.1 Unified Scale: Geometric Characterization of Communication and Sensing Channel States

To establish a unified benchmark for comparison, a channel-state metric is first needed that can simultaneously cover the requirements of both communication and sensing. Let the communication equivalent channel be $\mathbf{h}_c$ and the sensing equivalent channel be $\mathbf{h}_s$. Then the alignment degree of the two in a high-dimensional channel space can be expressed by a normalized inner product, namely the channel correlation:

$$\rho_{sc} = \frac{|\mathbf{h}_s^H \mathbf{h}_c|}{\|\mathbf{h}_s\|\|\mathbf{h}_c\|} = \cos\theta_{sc}, \qquad (29)$$

where θ_{sc} denotes the equivalent included angle between the communication

Figure 5

Figure 5: Figure 5

channel vector and the sensing channel vector. A larger ρ_{sc} usually means that the same transmit direction can simultaneously serve communication and sensing tasks; whereas a smaller ρ_{sc} indicates that the preferred channel subspaces of the two differ substantially, requiring more resource allocation or beam decomposition to coordinate their requirements. Furthermore, an ISAC transmit signal can be abstracted as a linear combination along the communication subspace direction $\mathbf{u}_c$ and the sensing subspace direction $\mathbf{u}_s$:

$$\mathbf{x} = x_c \mathbf{u}_c + x_s \mathbf{u}_s, \qquad (30)$$

where x_c and x_s denote the signal components allocated to the communication and sensing tasks, respectively. The core differences among various intelligent-environment technologies lie precisely in what mathematical mechanisms and geometric effects they use to act on this joint channel-state representation. As shown in Fig. 5, the light-blue arrow represents the original ISAC state, and the dark-blue arrow represents the state after reconstruction by the environment or hardware.

Figure 5 Controlling communication and sensing channel states via reconfigurable technologies. (a) RIS-assisted control; (b) UAV-assisted control; (c) reconfigurable antenna-assisted control

3.7.2 RIS/IRS-Assisted Control

By adjusting the reflection phases of a large number of passive elements, RIS/IRS can actively construct equivalent propagation paths between the base station and users. Denote the RIS phase-shift matrix as $\Phi = \mathrm{diag}(e^{j\phi_1}, e^{j\phi_2}, \ldots, e^{j\phi_N})$. The equivalent communication and sensing channels under RIS assistance can be written respectively as:

$$\mathbf{h}_c^{\mathrm{RIS}} = \mathbf{h}_c^d + \mathbf{G}_c \Phi \mathbf{g}, \quad \mathbf{h}_s^{\mathrm{RIS}} = \mathbf{h}_s^d + \mathbf{G}_s \Phi \mathbf{g}, \qquad (31)$$

where $\mathbf{h}_c^d$ and $\mathbf{h}_s^d$ are the possible direct-link channels, $\mathbf{G}_c$ and $\mathbf{G}_s$ denote the propagation matrices from the RIS toward the communication receiver and the sensing receiver, respectively, and $\mathbf{g}$ is the incident channel from the base station to the RIS. By optimizing the phase-shift matrix Φ, the RIS reconstructs the phases of the reflected paths, thereby changing the orientation of the composite channel vector in a high-dimensional space. The optimization objective of this process can naturally be summarized as maximizing the correlation between the communication and sensing channels:

$$\max \rho_{sc}^{\mathrm{RIS}} = \frac{\left|(\mathbf{h}_s^{\mathrm{RIS}})^H \mathbf{h}_c^{\mathrm{RIS}}\right|}{\|\mathbf{h}_s^{\mathrm{RIS}}\| \, \|\mathbf{h}_c^{\mathrm{RIS}}\|}. \quad (32)$$

From a geometric perspective, the role of the RIS can be approximately understood as regulating the directions and correlation of the equivalent channels, rather than strictly rotating the transmit signal vector: $\mathbf{x} \to \mathbf{R}(\Delta\theta)\mathbf{x}$. Its main effect is to bring the communication-channel direction and the sensing-channel direction closer to one another, i.e., $\theta_{sc}^{\mathrm{after}} < \theta_{sc}^{\mathrm{before}}$, or equivalently $\rho_{sc}^{\mathrm{after}} > \rho_{sc}^{\mathrm{before}}$. In Fig. 5(a), this mechanism is manifested as the light-blue arrow becoming a dark-blue arrow after rotation, with a significant change in direction and becoming more aligned with the jointly favorable sensing-communication direction. It is worth noting that this mechanism also explains the unique requirement of RIS-assisted sensing: simply pursuing a high correlation gain may conflict with multi-target separability, because the latter requires the channel to have a higher rank structure to support the effective separation of multiple parameters.

3.7.3 UAV-Assisted Control

Different from RIS, which changes the channel direction through phase control, mobile platforms such as UAVs mainly influence the propagation conditions through reconstruction of their three-dimensional spatial positions. Denote the UAV position as $\mathbf{q}$. The equivalent communication and sensing channels under its assistance can be abstracted as:

$$\mathbf{h}_c^{\mathrm{UAV}}(\mathbf{q}) = \sqrt{\beta_c(\mathbf{q})}\tilde{\mathbf{h}}_c(\mathbf{q}), \quad \mathbf{h}_s^{\mathrm{UAV}}(\mathbf{q}) = \sqrt{\beta_s(\mathbf{q})}\tilde{\mathbf{h}}_s(\mathbf{q}), \quad (33)$$

where $\beta_c(\mathbf{q})$ and $\beta_s(\mathbf{q})$ are the large-scale channel gains for communication and sensing associated with the UAV position, and $\tilde{\mathbf{h}}_c(\mathbf{q})$ and $\tilde{\mathbf{h}}_s(\mathbf{q})$ are normalized small-scale fading components. Typically, the large-scale gains follow a power-law decay with distance: $\beta_c(\mathbf{q}) \propto d_c(\mathbf{q})^{-\alpha_c}$, $\beta_s(\mathbf{q}) \propto d_s(\mathbf{q})^{-\alpha_s}$. The core of UAV trajectory optimization is

Table 2 Geometric and Mathematical Abstraction Comparison of Core Control Mechanisms in Smart Environments

Technology	Core Control Mechanisms	Mathematical Abstraction	Primary Optimization Variable	Intuitive Interpretation
RIS/IRS	Rotation	$\mathbf{x} \to \mathbf{R}(\Delta\theta)\mathbf{x}$	RIS phase shift	Adjusting communication and sensing channel directions
UAV/Mobile Platform	Scaling	$\mathbf{x} \to \alpha(\mathbf{q})\mathbf{x}$	UAV position $\mathbf{q}$	Changes distance, LoS conditions, and blockages, thereby adjusting channel gain
Reconfigurable Antenna	Shape Reshaping	$\mathbf{x} \to \mathbf{A}(\omega)\mathbf{x}$	Antenna state ω	Modifies radiation patterns and spatial component weights, reallocating energy more effectively

The objective is to find a spatial position that can simultaneously improve the quality of the communication and sensing links:

$$\max_{\mathbf{q}} \ \eta_c \|\mathbf{h}_c^{\mathrm{UAV}}(\mathbf{q})\|^2 + \eta_s \|\mathbf{h}_s^{\mathrm{UAV}}(\mathbf{q})\|^2 + \eta_\rho \rho_{sc}^{\mathrm{UAV}}(\mathbf{q}), \qquad (34)$$

where η_c, η_s, and η_ρ are the weighting coefficients of the respective terms. At the abstract level, the dominant effect of UAV position adjustment can be approximately understood as regulating link gain by changing the propagation distance and blockage state. This effect can be modeled as a multiplicative factor $\alpha(\mathbf{q}) > 0$, whose value may increase relative to a certain reference position, i.e., $\alpha(\mathbf{q}) > 1$, or may decrease, i.e., $\alpha(\mathbf{q}) < 1$. Therefore, the geometric abstraction of UAV-assisted control is mainly a first-order scaling operation: $\mathbf{x} \to \alpha(\mathbf{q})\mathbf{x}$, $\alpha(\mathbf{q}) > 0$. Its advantage lies in establishing or strengthening line-of-sight links to improve the link budget, and its primary role is gain regulation. However, in practical ISAC systems, the UAV position also synchronously changes the observation angles of multiple static base stations and targets, and therefore also has an important geometric reconstruction effect.

3.7.4 Reconfigurable-Antenna-Assisted Control

Reconfigurable-antenna technology introduces a new type of control degree of freedom distinct from surface phase and platform position, namely the physical position of antenna units and the array geometry. Denote the state parameter of the reconfigurable antenna by ω (which may cover port activation positions, radiation modes, or polarization states). Its effect can be characterized by a spatial filtering or mode-selection matrix $\mathbf{A}(\omega)$:

$$\mathbf{h}_c^{\mathrm{RA}} = \mathbf{A}(\omega)\mathbf{h}_c, \qquad \mathbf{h}_s^{\mathrm{RA}} = \mathbf{A}(\omega)\mathbf{h}_s. \qquad (35)$$

From the perspective of beamforming, the radiation gains in the communication direction and sensing direction are respectively $G_c(\omega) = |\mathbf{a}_c^H \mathbf{w}(\omega)|^2$ and $G_s(\omega) = |\mathbf{a}_s^H \mathbf{w}(\omega)|^2$, where $\mathbf{a}_c$ and $\mathbf{a}_s$ are the array response vectors in the corresponding directions, and $\mathbf{w}(\omega)$ is the radiation weight vector determined by the antenna state. The optimization objective of a reconfigurable antenna is no longer simply to rotate directions or increase modulus lengths, but rather to redistribute the available energy among different spatial components so as to maximize the effective energy useful for the current communication and sensing tasks:

$$\max_{\omega} \; \eta_c |\mathbf{a}_c^H \mathbf{w}(\omega)|^2 + \eta_s |\mathbf{a}_s^H \mathbf{w}(\omega)|^2. \qquad (36)$$

Further expand the ISAC signal as $\mathbf{x} = x_c \mathbf{u}_c + x_s \mathbf{u}_s + \mathbf{x}_\perp$, where $\mathbf{x}_\perp$ denotes an ineffective spatial component that contributes weakly to the current communication and sensing tasks. The essence of reconfigurable-antenna control is to suppress ineffective components and enhance effective components. Its dominant mechanism can be summarized as a first-order "response reshaping" : $\mathbf{x} \to \mathbf{A}(\omega)\mathbf{x}$. By optimizing ω, the ineffective spatial component $\mathbf{x}_\perp$, which contributes weakly to the tasks, is suppressed, while the effective components x_c and x_s are enhanced, thereby making $|x_c^{\mathrm{after}}|^2 + |x_s^{\mathrm{after}}|^2$ higher after optimization than $|x_c^{\mathrm{before}}|^2 + |x_s^{\mathrm{before}}|^2$. In Fig. 5(c), this is manifested as the originally dispersed broad beam being transformed, after reconstruction, into a focused narrow beam; the energy is re-concentrated in directions jointly effective for communication and sensing, and the ineffective components are significantly reduced.

3.7.5 Comparative Analysis of Mechanisms

Summarizing the above analysis, the mathematical abstractions and geometric intuitions of the three core smart-environment control technologies can be summarized as Table 2. Among them, RIS/IRS mainly changes the coherent superposition relationship among different propagation paths through surface phase and amplitude control, and thus is often manifested as adjustment of the equivalent channel direction or correlation; however, its configuration also synchronously changes the channel modulus length, spatial correlation, and effective rank. UAVs and other mobile platforms mainly change propagation through position adjustment.

propagation distance, blockage state, and large-scale link gain, and at the same time may also change the angle of arrival, multiple static baselines, and target-observation geometry. Reconfigurable antennas mainly reshape the spatial response through adjustments of antenna position, array aperture, radiation mode, or polarization state, but their specific impact on gain and rank structure depends on the propagation environment and feasible configurations. Therefore, Table 2 summarizes the dominant control dimensions of different technologies under typical conditions, rather than mutually exclusive functional categories. The geometric expressions in the table should be understood as a normalized indication; they do not mean that a certain class of technology can only produce a single type of channel variation, nor do they guarantee that all communication and sensing indicators will improve simultaneously after environmental reconstruction.

3.8 Challenges of Collaborative Intelligent Environment Control

The effective combination of the above technologies can actively adapt to the wireless propagation environment. Based on the main functions and objectives of these intelligent technologies, this paper summarizes and classifies them as shown in Table 3. They each differ significantly in controllable dimensions, core value for communication and sensing, and the bottlenecks they face, while also being mutually complementary. By exploiting these commonalities and differences and carrying out collaboration in terms of time, energy, cost, and other aspects, the radio environment can be managed more finely. If intelligent metasurfaces, mobile platforms, and reconfigurable antennas are further incorporated into this framework, a more general "collaborative intelligent environment" system can be formed: fixed infrastructure is responsible for long-term coverage and stable control; mobile platforms are responsible for geometric compensation and hotspot support; movable arrays are responsible for local rapid reconstruction; and multi-station networks are responsible for global scheduling and information fusion. At this point, the object of system design is no longer a single device, but a collaborative control network spanning nodes, time scales, and layers.

Taking the collaboration between UAVs and reconfigurable intelligent surfaces (RISs) as an example: the two can jointly create virtual line-of-sight channels to extend the coverage of sensing and communication. With the channel-gain improvement brought by RISs, the need for UAVs to approach users or targets in order to guarantee link quality can be reduced, thereby shortening flight distance, reducing power consumption, and extending charging intervals[^62]. Reference [63] gives an example architecture and proposes a UAV-assisted RIS framework to maximize network throughput. On the other hand, fluid antenna systems can dynamically adjust antenna positions according to UAV trajectories and

RIS phase configurations, thereby more efficiently exploiting both random environmental scattering and controllable environmental reflection; conversely, the phase of the RIS can also be optimized for antenna positions to obtain stronger signal power and more accurate passive beam focusing. However, because of the deep coupling among variables, jointly optimizing the mobile base-station trajectory, RIS element phases, and FAS antenna positions is mathematically highly challenging[^64], which also brings new opportunities for fully unleashing the potential of intelligent environments. It is worth noting that, while more resource collaboration improves the flexibility of radio-environment management, it will also inevitably introduce more frequent interactions among devices and more complex channel-estimation procedures. This exactly corresponds to the common bottlenecks faced by the multiple types of technologies in Table 3 in terms of CSI acquisition, estimation accuracy, and control overhead[^65]. Therefore, when conducting environmental control based on near-real-time radio maps, a key issue is how to realize collaborative propagation engineering with heterogeneous intelligent technologies under low computational complexity and low signaling overhead[^66]. In addition, to provide efficient, reliable, and robust control services and meet the dynamic needs of tasks, a user-centric collaborative intelligent propagation mechanism remains a research challenge that urgently needs breakthroughs.

4 Core Mechanisms of Mutualistic Collaboration Between Intelligent Environments and ISAC

4.1 Intelligent Environments Empower ISAC

4.1.1 Coverage Expansion and Virtual Line-of-Sight Reconstruction

The most intuitive gains of intelligent environments come from line-of-sight reconstruction and blockage avoidance. For communication, this is the most common link-enhancement mechanism in traditional RIS research; for sensing, its significance is even more prominent, because sensing echoes usually undergo two-way propagation, resulting in greater path loss and more obvious blind zones. By deploying fixed surfaces, target-mounted surfaces, or mobile platforms, the system can establish virtual LoS links in originally invisible regions, improve the detectability of blocked targets, and significantly improve the continuity of localization and tracking[^7-^10,^19]. In network-level systems, such coverage expansion can also bring better multi-static geometry and is conducive to improving the robustness of target estimation[^67].

Furthermore, UAV-assisted ISAC shows that, in intelligent environments, mobile platforms are not merely temporary relays or blind-spot nodes, but can act as movable geometric reconstructors[^68]. Through joint design of trajectory, hovering position, and beam direction, UAVs can proactively change the LoS relationships among base stations, users, and targets, thereby simultaneously improving communication coverage and sensing observability in blocked areas, edge areas, and dynamic-target scenarios. Related

Table 3 Roles and bottlenecks of key smart-environment technologies and architectures in integrated sensing and communication

Technology	Controllable Dimensions	Core Value for Communication	Core Value for Sensing	Main Bottleneck
Fixed RIS/IRS	Phase/Amplitude/Reflection-Transmission Mode	Bypass blockage, enhance link gain, reduce interference	Establish virtual LoS, extend blind-zone coverage, improve target detectability	Difficulty in CSI acquisition, phase update overhead, trade-off between high-rank observation and strong LoS requirement
Vehicle-mounted RIS	Target echo direction, reflection/transmission energy allocation	Improve coverage inside/outside vehicle, support high-mobility links	Enhance small-RCS target echo, enable cooperative localization and tracking	Pose uncertainty, control feedback delay, complex hardware integration
Hybrid/Self-Sensing RIS	Local sensing, preprocessing, limited active gain	Reduce base-station training and control overhead	Support blind-zone detection and surface-side state awareness	Energy consumption, cost, complex surface-side computation and fusion design
UAV/Mobile Platform	Position, trajectory, hovering point, viewpoint	Hotspot coverage, link compensation, topology reconfiguration	Enhance multistatic geometry, increase observation-angle diversity	High flight energy consumption, slow control timescale, strong platform safety constraints

Technology	Controllable Dimensions	Core Value for Communication	Core Value for Sensing	Main Bottleneck
Reconfigurable Antenna	Port positions, array shape, aperture geometry	Select favorable channel, suppress interference, improve spatial-division efficiency	Enhance angle–range resolution, near-field focusing, and target resolvability	Strong geometry–channel coupling, high estimation and control complexity
Multi-BS Cooperative Network	Cooperative cluster, association, backhaul and task allocation	CoMP transmission, coverage enhancement, network-level interference management	Multistatic sensing, wide-area coverage, observation fusion	Backhaul limitation, synchronization difficulty, complex performance evaluation and optimization

Research has pointed out that the core challenges of UAV-enabled ISAC lie not only in link-gain improvement, but also in how to jointly optimize the movement trajectory, communication resources, and sensing-task scheduling under constraints on UAV payload, energy consumption, flight speed, and LoS air-ground channels. Therefore, in smart-environment-enhanced ISAC, UAVs are more suitable as topology and geometric control units for medium- and slow-timescale operations, rather than merely as aerial base stations or reflecting nodes.

4.1.2 Channel sparsity and correlation reshaping

The preferences of communication and sensing for channel structures are not completely consistent, and this is precisely one of the mechanisms most worthy of attention in smart-environment-enhanced ISAC. Multi-user communication usually expects user channels to have as low correlation as possible, so as to support spatial multiplexing and interference suppression; sensing, by contrast, requires sufficient geometric diversity and a high-rank observation structure in target-observable directions, so as to realize reliable estimation of angle, range, velocity, and even scattering characteristics. Reference [8] explicitly points out that, in RIS-assisted sensing, an overly ideal sparse LoS channel between the transceiver and the RIS may instead be unfavorable for multi-parameter estimation, because the parameters of multiple targets are difficult to separate effectively through low-rank mapping. It can thus be seen that environmental control is not merely "power amplification" ; more importantly, it performs "structure reshaping." This understanding is of fundamental significance for subsequent optimization-objective design.

To illustrate this conflict more intuitively, consider a simple RIS dual-mode scenario. The first mode $\mathbf{u}_1$ is aligned with the dominant LoS direction of the communication user and can provide the maximum communication gain; the second mode $\mathbf{u}_2$ provides an independent target-observation direction and is mainly used to increase sensing geometric diversity. Assume that the two are orthogonal, and let $\rho \in [0, 1]$ denote the normalized effective reflection resource allocated to the first mode. Under the normalized model, the communication SNR can be written as

$$\gamma_c(\rho) = \rho\gamma_{\max}. \qquad (37)$$

For a sensing task requiring estimation of two mutually coupled parameters, the corresponding Fisher information matrix can be simplified as

$$\mathbf{J}_s(\rho) = J_0\left[\rho\mathbf{u}_1\mathbf{u}_1^H + (1-\rho)\mathbf{u}_2\mathbf{u}_2^H\right], \qquad (38)$$

and thus

$$\det(\mathbf{J}_s(\rho)) = J_0^2\rho(1-\rho). \qquad (39)$$

When only the communication SNR is maximized, the optimal solution is $\rho = 1$. At this point $\gamma_c = \gamma_{\max}$, but $\det(\mathbf{J}_s) = 0$, and the sensing observation degenerates into a rank-one structure. For joint estimation tasks involving two or more parameters, at least one parameter direction has no finite CRLB, or the corresponding CRLB tends to infinity. Conversely, the sensing D-optimal configuration is $\rho = 1/2$, at which the determinant of the Fisher information matrix reaches its maximum, but the communication SNR is reduced by 3 dB relative to the communication-optimal configuration. Define the normalized communication and sensing performance respectively as

$$g_c = \frac{\gamma_c}{\gamma_{\max}} = \rho, \qquad g_s = \frac{4\det(\mathbf{J}_s)}{J_0^2} = 4\rho(1-\rho), \qquad (40)$$

then $\rho \in [1/2, 1]$ delineates the Pareto boundary between the two. Changing the weights of communication and sensing in the weighted utility function is equivalent to selecting different operating points along this boundary. This simplified result shows that a strong LoS link itself is not necessarily beneficial to multi-parameter sensing; if environmental control allocates all degrees of freedom to coherent gain superposition, it may simultaneously cause rank degradation in the observation. Therefore, in practical design, a controllable structural tradeoff must be maintained between array gain and independent observation dimensions.

From a network-level perspective, channel rank and correlation reshaping depend not only on RIS phase shifts or single-site array structures, but are also closely related to base-station cooperation modes and antenna topology. Existing studies on cooperative ISAC networks have shown [69] that multi-base-station joint transmission and distributed MIMO sensing can simultaneously alter communication interference structure and target observation geometry at the network scale, thereby forming new tradeoff relationships among communication coverage, positioning accuracy, and cooperative beamforming scale. Furthermore, the evolution of antenna topology from massive MIMO to cell-free MIMO also reflects a similar mechanism: centralized large-scale arrays are more conducive to coherent beamforming gain, whereas distributed arrays enhance geometric diversity by shortening user/target access distances and increasing spatial viewing angles. Therefore, "structural reshaping" in intelligent environments includes not only electromagnetic response control on physical surfaces, but also system-level reconfiguration of network antenna topology, cooperative beamforming allocation, and multi-site observation structures.

4.1.3 Communication-Sensing Mutual Gain

(1) Sensing-assisted communication. Sensing-assisted communication is one of the most practically valuable mechanisms in ISAC mutual gain, especially suitable for high-mobility and highly dynamic scenarios. Reference [9] proposed a two-stage protocol for vehicular networks: in the joint communication-and-sensing stage, a STAR-RIS is used to reflect part of the energy to the side units of the loop to obtain vehicle-state information; in the subsequent pure-communication stage, more accurate beam and phase configurations are then performed based on the existing sensing results, thereby improving the overall achievable rate. This indicates that the additionally invested sensing resources are not merely a "cost,"but may be converted into net gains through reduced subsequent beam-tracking overhead, lower misalignment probability, and improved link robustness. Generally, as long as the communication benefit brought by sensing exceeds the time, power, and control overhead of sensing itself, sensing-assisted communication is worthwhile; otherwise, a pure communication strategy may be superior [8,9]. Therefore, the net-gain condition of closed-loop beam management can be analyzed. Consider a beam update period of length T. Traditional exhaustive training needs to search N_b candidate beams, with each beam occupying training time τ_p. If the effective data rate obtained after training is R_0, then the average throughput after deducting training overhead is

$$\overline{R}_{\mathrm{ex}} = \left(1 - \frac{N_b \tau_p}{T}\right) R_0. \qquad (41)$$

Figure 6. Simulation scenarios.

Figure 6: Figure 6. Simulation scenarios.

The closed-loop scheme uses ISAC sensing results to predict vehicle position and blockage state, and needs to verify only L candidate beams, where $L \ll N_b$. Let the additional sensing and control overheads be τ_s and τ_c, respectively; the probability of correct beam prediction be p; and the effective rate under prediction mismatch be $R_m < R_0$, where R_m also reflects the effects of beam mismatch, fallback training, or short-term interruption. Then the net throughput of the closed-loop scheme is

$$\overline{R}_{\text{cl}} = \left(1 - \frac{L\tau_p + \tau_s + \tau_c}{T}\right)\left[pR_0 + (1-p)R_m\right]. \qquad (42)$$

Figure 6 Simulation scenarios.

Therefore, the condition for closed-loop mutual benefit to produce a net gain is

$$p > \frac{\dfrac{1 - N_b\tau_p/T}{1 - (L\tau_p + \tau_s + \tau_c)/T} R_0 - R_m}{R_0 - R_m}. \qquad (43)$$

For example, if exhaustive training accounts for 20% of the update period, the candidate-beam verification, sensing, and control overhead of the closed-loop scheme together account for 5%, and $R_m = 0.2R_0$ can still be maintained when a mismatch occurs, then the closed-loop prediction accuracy needs to be higher than about 80.3%. When $p = 0.9$, $\overline{R}_{\text{cl}} = 0.874R_0$, whereas $\overline{R}_{\text{ex}} = 0.8R_0$, corresponding to a net throughput improvement of about 9.25%. This normalized example is used only to illustrate the criterion for net gain; the specific boundary still depends on the vehicle speed, the number of beams, the control delay, and whether sensing information can be reused with communication signals.

(2) Communication-assisted sensing. Correspondingly, communication services can in many cases also support sensing in return. On the one hand, the communication signal itself is a potential sensing-probing waveform; the radiated energy of the communication signal in non-target directions, neighboring-cell signals, and even interference terms may, after proper design, be converted into additional illumination sources or auxiliary observations [8, 11]. On the other hand, the edge computing, information backhaul, and data-fusion capabilities provided by the communication network enable multi-node sensing results to be aggregated and processed more rapidly, thereby supporting low-latency target tracking and environmental updating [11, 13]. This point is particularly prominent in multi-base-station cooperative ISAC: the organizational capability of the communication network determines whether multiple static echoes can be effectively aggregated; therefore, in a certain sense, network communication capability itself is also part of sensing quality.

4.1.4 Comprehensive example: collaborative empowerment of ISAC by multi-intelligent-environment technologies To intuitively demonstrate the collaborative efficacy of intelligent-environment technologies in ISAC, this subsection takes the joint optimization of UAV, RIS, and FAS as an example and provides a comprehensive simulation-verification example. The purpose of this example is not to exhaust all parameter configurations, but to reveal the incremental gains brought by the collaboration of multiple technologies and the basic tradeoff between communication and sensing performance.

As shown in Fig. 6, an ISAC system composed of a single UAV, a single RIS, and multiple FAS users is considered. The UAV simultaneously assumes the roles of communication base station and sensing receiver, and its flight trajectory can be dynamically optimized; the RIS is deployed on the ground and contains 1000 reflecting elements, which are used to establish virtual line-of-sight links between the UAV and users/targets; each user is equipped with an FAS, which can switch the antenna position among 100 discrete ports to obtain better channel conditions. Under the premise of satisfying the sensing-echo signal-to-noise-ratio threshold, the system maximizes the achievable communication rate. The maximum horizontal flight speed of the UAV is 30 m/s, the flight altitude is 30 m, the noise power at the user is −70 dBm, the noise power at the UAV is −90 dBm, and the maximum transmit power is 1 W.

Figure 7 gives the curves of the communication rate versus the sensing SNR threshold under different intelligent-environment configurations. It can be seen that the scheme in which the three technologies cooperate obtains the highest rate over the entire sensing-SNR range; its performance is significantly better than that of the unaided baseline scheme, and also better than schemes assisted by only one or two technologies. This gain comes from collaboration at three levels: the UAV shortens the propagation distance through trajectory optimization and improves the observation geometry, while the RIS compensates for blockage through phase design and enhances ···

Figure 7 ISAC performance improvement by smart environment.

···enhance the effective signal power; FAS further improves link quality by selecting ports to exploit spatial channel fluctuations.

At the same time, as the sensing SNR threshold increases, the achievable rates of all schemes relying on smart-environment assistance show a downward trend. This is because the system allocates more resources to the sensing task to meet high-accuracy sensing requirements, thereby squeezing the degrees of freedom available for communication. When the sensing SNR threshold exceeds a certain level, adjustments based solely on RIS phases and FAS ports can no longer satisfy the sensing-accuracy requirement; the UAV must further approach the target to shorten the two-way propagation loss. Although this positional adjustment is beneficial for sensing, it may increase the path loss or interference for communication users, causing the communication rate to drop more rapidly. This phenomenon also indicates that environmental control cannot optimally serve communication and sensing simultaneously under all conditions; rather, a controllable trade-off space must be retained between the two. The above simulation example shows that the performance gain brought by smart-environment technologies to ISAC is the result of multidimensional, multi-technology synergy, but this synergy is also accompanied by inherent constraints arising from competition between communication and sensing resources. Therefore, in practical system design, one should not pursue the extreme gain of a single technology alone; instead, joint trade-offs should be made among communication rate, sensing accuracy, and control overhead according to the specific task requirements.

4.2 ISAC-Empowered Smart-Environment Control

4.2.1 Closed-Loop Control for Overhead-Aware Sensing

Unlike simply pursuing an upper performance bound, the practical advantage of ISAC-enhanced smart environments is often reflected in "obtaining more stable comprehensive gains with acceptable overhead." If every surface phase update, UAV position adjustment, and array reconfiguration depends on high-dimensional global CSI, the overhead of environmental control itself may overwhelm its gains. The unique value of ISAC lies in the fact that, through continuous sensing of user locations, target states, blockage distributions, and environmental evolution, the system can trigger local updates only when necessary, thereby realizing low-overhead, task-related, and multi-timescale closed-loop control

$$10, 11, 13$$

. Therefore, when evaluating whether a smart environment and ISAC are truly effective, one should not look only at instantaneous rate or one-time localization error; instead, the control cost, training overhead, and update frequency should be explicitly incorporated.

Different intelligent propagation-engineering technologies realize low-overhead control in their own distinctive ways. For example, integrating sensors into RIS can enhance its ability to analyze echo signals, enabling sensing results to support adaptive passive beamforming design without control signals from the base station. Using sensing for user discovery can also reduce the interaction between the UAV and users, facilitating real-time trajectory design. In addition, sensing results related to the environment help realize wireless adaptation of FAS without CSI estimation

$$70$$

. Moreover, sensing results can be used to construct a three-dimensional map of the environment, including both dynamic and quasi-static information. With the aid of ray-tracing techniques, this map models wave propagation, thereby reducing the requirements for environmental control and ultimately lowering overhead. Beyond assisting intelligent propagation engineering in a single cell, ISAC can also reduce, for example, the time/power consumption associated with handover between UAV-mounted base stations and terrestrial base stations, thereby saving time and power resources.

4.2.2 Predictive Resource Allocation

Based on estimates of the dynamic characteristics of users and targets as well as the requirements of sensing and communication services, predictive resource allocation for UAVs, RISs, and FASs can reduce service latency and improve reliability. However, because variables are mutually coupled, jointly optimizing resource allocation across multiple nodes is highly challenging. A feasible approach is to track only the states of users and targets related to the current communication and sensing tasks, and to integrate the local observations of each node to predict their motion trajectories and service requirements[^11]. On this basis, network resources, user and target scheduling, and intelligent environment configuration can be jointly optimized[^71]. By jointly optimizing network resource allocation, user scheduling, and the intelligent environment, high-quality sensing and communication services can be achieved. In addition to predictive design based on sensing results, prediction based on data-transmission service requirements can also support more efficient resource allocation.

In high-speed vehicular-network scenarios, the trajectories of vehicles traveling along roads exhibit strong regularity. An ISAC system can continuously sense and acquire vehicle position, speed, and lane information, and combine these with road maps to predict the vehicle' s driving route over the next several seconds. Based on this prediction, roadside RISs can switch their phase configurations in advance to the precomputed optimal values for the region that the vehicle is about to enter; base-station beams can also be steered in advance toward the predicted direction, while communication terminals can pre-complete service base-station selection and association[^72].

4.2.3 Obstruction-Aware Sensing for Channel Regulation

Although the above potential performance-improvement prospects are promising, they may be compromised by potential obstructions. Therefore, obtaining obstruction information through sensing is highly beneficial for realizing reliable and robust sensing and communication services in scenarios with large numbers of obstacles. Based on estimates of user motion, UAV positions can be optimized using accurate environmental information so as to avoid obstructions and reduce propagation loss. For near-field sensing and communication, antennas or surface arrays may be partially obstructed[^11]. In other words, in near-field or extremely large-scale array scenarios, affected by obstruction and spatially non-stationary propagation, different users may see only part of the array, i.e., they have different array-visibility regions. In addition, large targets themselves may also cause potential obstructions; thus intelligent propagation engineering should take obstruction into account during design. Conversely, obstruction can also be exploited to significantly reduce inter-user and inter-cell interference. Therefore, the environmental-sensing capability brought by ISAC provides a breakthrough capability for propagation control based on user location to avoid service interruption.

In obstacle-dense scenarios, with the aid of ISAC sensing capability, the system can continuously monitor the motion states of the main scatterers and potential obstacles in the environment. Once it is predicted that an obstacle will obstruct the current service path within the next several hundred milliseconds, the system can switch the RIS phase configuration in advance to an alternative reflection path, or associate the user with another unobstructed RIS[^73]. In addition, through continuous sensing of the environment, ISAC can construct a dynamic three-dimensional obstruction map for UAVs, marking the current and predicted obstruction relationships between each aerial location and the target ground region. Based on this map, the UAV can identify the obstruction boundaries of buildings on both sides through sensing, and precisely select its hovering point within a "line-of-sight window," thereby obtaining a significant improvement in link quality with very small position adjustment[^74].

5 Intelligent Environment and ISAC: Evolution from Link Design to Network Collaboration

The discussion in the preceding chapters has mainly focused on mechanisms involving a single link or a local system. However, the full value of intelligent-environment-enhanced ISAC should be measured at the network scale. When the system expands from a single station and a single surface to a large-scale network with multiple base stations, multiple RISs, multiple UAVs, and multiple users, a series of new problems that are not significant at the link level begin to emerge, while collaborative gains unavailable at the link level also appear[^69,^75].

5.1 New Design Considerations

5.1.1 Multidimensional Optimization Variables Compared with traditional ISAC systems, a salient feature of intelligent-environment-enhanced systems in the optimization space is the rapid expansion of variable dimensions and the deep heterogeneity of variable types[^76]. Specifically, the optimization variables can be divided into three levels. At the link level, traditional optimization objects still exist, including transmit beamforming, receive filtering, power allocation, time–frequency resource allocation, and waveform-parameter configuration, which mainly act on the instantaneous transmission quality of a single communication or sensing link. At the environment level, the introduction of intelligent environments brings entirely new controllable degrees of freedom: for example, phase/amplitude configuration and reflection/transmission operating-mode selection for RISs and STAR-RISs, hybrid deployment strategies for active and passive elements, and the three-dimensional positions, hovering points, and flight ⋯

trajectories, and the port activation positions or array geometries of fluid antenna systems. These variables directly change the boundary conditions of electromagnetic-wave propagation, turning the wireless environment itself from a passive random factor into a programmable optimization resource. At the network level, the system must also make global decisions on the scale and member composition of cooperative base-station clusters, user access and association strategies, cross-node allocation of sensing and communication tasks, independent or joint partitioning of sensing-cooperation clusters and communication-cooperation clusters, as well as resource allocation on backhaul links and cross-node information-fusion strategies

$$10, 11, 13$$

. The above three categories of variables belong to different physical entities, span multiple time scales from microsecond-level waveform adjustment to second-/minute-level node deployment, and exhibit deep hierarchical coupling and constraints among one another. Such cross-level, multi-scale joint optimization makes the original problem typically display complex characteristics such as high nonconvexity, mixed-integer structure, stochastic dynamics, and partial observability.

5.1.2 Hierarchization of Performance Metrics

References

$$11, 13$$

point out that network-level integrated communication and sensing urgently requires the establishment of a new performance evaluation system, and this requirement becomes even more prominent and pressing after the introduction of intelligent environments. Traditional performance metrics are mostly oriented toward the design of individual communication or sensing links, making it difficult to characterize the cooperative gains and system constraints of intelligent environments under multiple nodes and multiple scales. Specifically, at the single-link level, commonly used metrics include achievable rate, signal-to-interference-plus-noise ratio of communication users, bit error rate, output signal-to-noise ratio of sensing filters, minimum mean-square error, Cramér-Rao lower bound, and detection probability; these emphasize measurement of point-to-point transmission quality or sensing accuracy. When the perspective rises to the local-system level, the evaluation system must further incorporate metrics such as the proportion of sensing blind zones, continuity of target tracking, regional coverage range, and beam training overhead, so as to reflect the completeness and stability of local sensing and communication services under intelligent metasurface deployment or UAV assistance. At the network scale, the focus of system design shifts from a single link or local region to the performance and operability of the entire network. At this point, global metrics such as CRLB coverage probability, spectral efficiency of joint communication-and-sensing regions, network energy efficiency, task completion delay, and cooperative backhaul load become indispensable. Together, these metrics characterize the comprehensive tradeoff among resource efficiency, service reliability, and deployment cost in the network. In other words, network-level ISAC empowered by intelligent environments requires system evaluation to move from the traditional "link-optimal" paradigm, through the transition of "region-effective," and ultimately toward a global perspective of "network-operable." This is also a deep-seated reason why stochastic geometry, statistical coverage analysis, and average performance metrics have received increasing attention in recent years in network-level ISAC research

11, 13

: they can characterize the statistical properties of large-scale networks within a unified mathematical framework and provide theoretical guidance for deployment strategies and network-level resource optimization in intelligent environments.

5.2 New Opportunities

5.2.1 Advantages from Link to Network

(1) Multi-base-station sensing and geometric gain. Link-level sensing is usually limited by the viewpoint of a single station, and parameter estimation in certain directions may contain blind zones or insufficient accuracy. Multi-station cooperation at the network level naturally forms a multi-base-station sensing architecture, enabling targets to be observed simultaneously from multiple perspectives

11, 13

. The scaling-law analysis in Ref.

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shows that using N ISAC transceivers for cooperative sensing can improve localization accuracy by approximately $\ln^2 N$ times. If RISs and UAVs are further introduced, additional observation paths can be artificially created and multistatic geometries enriched, thereby breaking through the physical limitations of pure base-station cooperation.

(2) Structured utilization of network-level interference. Interference that is regarded as harmful at the link level may be transformed into a useful resource at the network level. For example, communication signals from neighboring stations can serve as additional non-cooperative illumination sources, enhancing the detection probability of targets; mutual interference between base stations that originally needed to be eliminated can, with proper temporal and spatial coordination, become a component of distributed radar

. This capability of "turning interference into resources" is unique to network-level systems and is also a potential gain that is difficult to exploit through purely link-level optimization.

(3) Cooperative coverage and load balancing. The sensing and communication loads of different nodes in a network are often uneven. Through cooperative scheduling in intelligent environments, some sensing or communication tasks of heavily loaded nodes can be offloaded to neighboring nodes that use RIS-reflected-path services, or the load can be balanced through temporary repositioning of UAVs. This network-level load elasticity cannot be achieved by link-level systems, and it also provides a new dimension for arguing the deployment value of intelligent environments.

(4) Cross-node information fusion and cognitive upgrading. Another important opportunity at the network level lies in deep fusion of multi-source information. The sensing data obtained by different nodes complement one another in time, space, and modality, and fusion at the data level or feature level can significantly enhance the completeness and robustness of environmental cognition. On this basis, the network can construct a global environmental state map that goes beyond the field of view of a single station, providing high-quality input for subsequent predictive control and task decision-making.

5.2.2 Potential Gains from Multi-Point Collaboration

In traditional multi-base-station cooperation, the essence is to improve performance through joint design at the signal level under a given propagation environment. Base-station locations are fixed and channels are determined by the environment; the dimension of cooperation is limited to the signal-processing space. The introduction of intelligent environments fundamentally changes this premise: RIS can reconfigure reflection paths, UAVs can change node topology, and FAS can adjust array geometry; therefore, the propagation environment itself becomes an optimizable variable.

When multiple intelligent-environment nodes work collaboratively, their gains are often not a simple linear superposition of the independent gains of each node, but may appear as nonlinear synergistic gains produced by the joint coupling of propagation paths, observation geometry, and interference structure. The deeper mechanism of this linkage lies in the fact that each intelligent node not only improves its local propagation conditions, but also creates a more favorable basis for cooperation for other nodes. A virtual line-of-sight path established by one RIS may just provide a better angle of incidence for another RIS; the deployment position of a UAV may open new spatial degrees of freedom for multiple FASs; and the port configuration of multiple FASs may in turn reduce the complexity of RIS phase optimization. This cooperative relationship of "mutual premise and mutual amplification" cannot be achieved by a single type of technology or by traditional multi-base-station cooperation, and it is also the core value increment of multi-node intelligent-environment cooperation. In this section, we outline several typical scenarios in which ISAC networks and intelligent environments can provide advantages.

(1) Multi-RIS cooperation: from single-hop reflection to multi-hop path stitching and sensing-gain cooperation. The coverage enhancement of a single RIS is limited by its relative geometric relationship with the base station and users. Moreover, in single-RIS-assisted sensing, all target echoes share the same reflection path, and overlap in elevation angle at the receiver, causing a bottleneck in multi-target resolution. Multiple RISs can bypass complex blockage through cascading or multi-path cooperation and expand coverage in deep-shadow regions. When the auxiliary paths have sufficient geometric differences and appropriate coding, synchronization, and fusion mechanisms are adopted, multiple RISs can provide richer observation dimensions and improve the separability of target echoes. However, their gains still depend on RIS deployment locations, array apertures, propagation loss, and observation geometry. Although a single RIS can also realize multi-static observation with the aid of arrays, time-varying coding, or near-field beams, its resolvability relies more strongly on aperture and time resources.

(2) Multi-UAV cooperation: from single-point coverage fill-in to continuous tracking. The coverage and sensing capability of a single UAV are limited by the viewing angle of a single platform, and observations of targets are often sparse and instantaneous. Multi-UAV cooperation can construct synthetic observation apertures in the air in formation, illuminating and receiving simultaneously or sequentially from multiple angles and altitudes over the target region. At the sensing level, this is equivalent to deploying a dynamically reconfigurable distributed radar network in the air: the observation results of different UAVs complement one another in time and space, enabling approximately all-azimuth continuous tracking and significantly reducing the probability of tracking loss caused by target motion or blockage. At the communication level, multiple UAVs can self-organize to form a dynamic aerial topology and provide seamless coverage for ground users. The spatial configuration of the formation itself is an optimization variable, and the baseline length and observation-angle distribution can be dynamically adjusted for specific target types, such as highly maneuverable small targets or low-speed large targets.

(3) Multi-FAS cooperation: from local port switching to spatial leakage suppression. A single FAS selects the optimal channel within a local space through port switching, and its gain is mainly reflected in improving the quality of a single link. When multiple FASs collaborate among multiple nodes, their potential is not limited to this. The antenna positions of multiple FASs can be jointly adjusted so that the equivalent channel matrices between different nodes exhibit a specific zero-space structure; that is, the transmitted signal forms a deep fade at the non-target receiver while maintaining high gain at the target receiver. This provides a potential path for physical-layer secure transmission that reduces reliance on artificial noise: under ideal channel controllability, the system is expected to reduce the receivable signal power of unauthorized receivers through spatial nulling or channel shaping. For ISAC scenarios, this "silencing" capability also means that interference from communication signals to sensing echoes can be effectively suppressed, while avoiding exposing the location of the sensing receiver through the communication waveform.

5.3 New Challenges

The potential of multi-node intelligent-environment linkage is enormous, but to move it from conceptual verification toward practical deployment, breakthroughs are needed on the following key contradictions.

(1) The exponential contradiction between synergistic gain and computational complexity. The essence of linkage gain is deep coupling among variables, which is precisely the source of its multiplication effect, but it also means that the coupling degree of the optimization problem and the difficulty of solution increase exponentially with the number of nodes. Taking multi-RIS joint phase design as an example: if each of K RISs has N elements, and each element has B discrete phases, then the computational complexity of exhaustive search is $O(B^{KN})$, which grows exponentially with K and N. Traditional alternating optimization methods are very prone to falling into local optima. More challenging still, the coupling relationship is not static: UAV movement changes the effective channel structure between RISs, and FAS port switching changes the array coupling matrix. Therefore, the value of linkage lies precisely in the most difficult-to-solve highly coupled regions, and how to approach the performance upper bound of these regions at an acceptable computational cost is the primary bottleneck for realizing linkage. Possible breakthrough directions include: multi-node relationship modeling based on graph neural networks (mapping optimization variables to graph nodes and using message-passing mechanisms to capture local coupling), hierarchical decoupling optimization

···(decomposing global linkage into tight intra-cluster coupling + loose inter-cluster coupling), and using sensing results as warm-start signals to reduce the search space.

(2) Environmental interference in collaboration. While multi-node collaboration creates desired linkage, it also introduces unintended environmental interference. The reflection path of one RIS may interfere with the target echo of another RIS; a strong LoS link established by a UAV may happen to introduce interference into an originally clean region; and port adjustment in multiple FASs may alter the channels between RISs and cause phase mismatch. Such "collaborative side effects" are essentially absent in link-level design, but at the network level they may seriously erode the linkage gain. The key difficulty is that the strength of interference and the linkage gain often have the same source; that is, a stronger linkage inevitably introduces stronger interference. How to strike a balance between "pursuing coupling" and "controlling interference" requires new optimization theory and interference-modeling tools.

(3) Conflict balancing in multi-agent decision-making. In network-level linkage, the control objectives of different intelligent nodes are not naturally consistent. An RIS serving communication seeks to maximize the received signal-to-noise ratio of users, whereas an RIS serving sensing needs to maximize the energy of echoes in a specific direction; the optimal hovering point of one UAV may block the sensing task of another UAV; and if FAS port selection prioritizes communication security, it may sacrifice the aperture diversity required for sensing. Such multi-agent and multi-objective conflicts can be formalized in traditional centralized optimization through weighted utility functions, but the choice of weights itself reflects task priorities, service levels, and system policy preferences. Therefore, it must be determined through explicit preference modeling or dynamic task-scheduling mechanisms; moreover, in actual operation, task priorities may vary dynamically over time. Establishing a multi-agent decision-coordination mechanism for dynamic priorities is a challenge that network-level linkage must face.

(4) Integration of collaborative clusters, signaling, and limited backhaul. Network-level collaboration must first determine which nodes participate in the current communication or sensing task. One feasible approach is to first screen candidate nodes according to large-scale channels, target visibility, and observation geometry, and then select the collaborative cluster $\mathcal{B}$ through net utility:

$$\mathcal{B}^{\star} = \arg\max_{\mathcal{B}} \left\{ U_{\mathrm{ISAC}}(\mathcal{B}) - \lambda_{\mathrm{bh}} C_{\mathrm{bh}}(\mathcal{B}) - \lambda_{\mathrm{syn}} C_{\mathrm{syn}}(\mathcal{B}) \right\}, \tag{44}$$

where U_{ISAC} denotes the benefit brought by communication rate, sensing information, or joint coverage, and C_{bh} and C_{syn} denote the backhaul and synchronization costs, respectively. To avoid frequent switching of collaborative clusters caused by user mobility or short-term blockage, practical algorithms must also introduce a switching-hysteresis threshold and a minimum dwell time, updating the collaborative cluster only when the marginal effect brought by adding a node exceeds the corresponding control cost.

Collaborative signaling can be organized hierarchically according to update rate. Slow timescale signaling mainly exchanges information such as node positions, target visibility, radio maps, long-term loads, and clock quality; medium timescale signaling exchanges collaborative clusters, user/target associations, task priorities, and resource budgets; fast timescale signaling exchanges only beam or surface-codebook indices, local estimation results, timestamps, and necessary synchronization correction quantities. This hierarchical approach avoids sharing full-dimensional CSI and raw sensing data in every time slot.

Information fusion under limited backhaul can be divided into three levels: signal-level, information-level, and decision-level. If each node has N_r receiving channels and collects N_s samples within one fusion period, the backhaul volume required to share raw signals usually grows as $O(|\mathcal{B}|N_r N_s)$, and relatively strict phase and time synchronization is required. For a d-dimensional target state, the information volume required to share a local Fisher information matrix or covariance is approximately $O(|\mathcal{B}|d^2)$, whereas the load of sharing only detection results or state estimates can be further reduced to $O(|\mathcal{B}|d)$.

When local observation conditions are independent, node b may upload the information matrix $\mathbf{J}_b$ and the information vector $\xi_b = \mathbf{J}_b\hat{\eta}_b$, and the fusion center computes accordingly

$$\mathbf{J}_{\mathrm{f}} = \sum_{b\in\mathcal{B}} \omega_b \mathbf{J}_b, \qquad \hat{\eta}_{\mathrm{f}} = \mathbf{J}_{\mathrm{f}}^{-1} \sum_{b\in\mathcal{B}} \omega_b \xi_b, \tag{45}$$

where ω_b can be set according to estimation reliability, quantization precision, and information timeliness. When the correlation between local estimates is unknown, conservative fusion methods such as covariance intersection must be adopted to avoid repeatedly counting correlated information. Therefore, the selection of the fusion level is essentially a tradeoff among backhaul capacity, synchronization capability, and sensing accuracy.

In summary, the evolution from single-station, single-link designs to multi-node network collaboration has brought new design considerations such as multidimensional-variable coupling and hierarchical performance metrics, and has also opened new opportunity windows such as multi-base-station sensing, structured use of interference, collaborative coverage, and cross-node information fusion. However, obtaining collaborative gain is not without cost: exponentially growing optimization complexity, unexpected environmental interference, conflicts in multi-agent decision-making, and limited backhaul and synchronization constraints constitute the main technical bottlenecks faced by current network-level intelligent-environment-enhanced ISAC. The following will further refine these structural challenges that cut across links, systems, and networks, and will look ahead to research directions in which major breakthroughs in this field are worthy of focus.

6 Design Paradigms for Intelligent Environment-Enhanced ISAC

6.1 Multi-Time-Scale Design Paradigm

This paper argues that multi-time-scale design is an important methodology for steering intelligent environment-enhanced ISAC toward implementability. An intelligent environment-enhanced communication–sensing integrated system is, in essence, a complex dynamic system spanning multiple time scales. Table 4 summarizes this multi-time-scale control perspective from four dimensions: time scale, representative variables, triggering basis, and suitable methods. In general, beams and receive filters are fast-time-scale variables and can be updated on a short time scale; surface phase shifts, STAR-RIS transmission ratios, and local port selection belong to the medium-fast time scale; UAV trajectories, base-station cooperative clusters, and platform deployment belong to the medium-slow time scale; while radio maps, digital-twin scenario models, and long-term deployment strategies belong to the slow time scale. On the fast time scale, the system must rapidly adjust transmit beams, receive filters, and partial power allocation according to instantaneous channel fluctuations and short-term sensing results. Convex optimization, iterative beam design, or low-dimensional online updating are usually adopted to adapt to rapid channel variations. On the medium-fast time scale, when user or target locations change significantly, or when blockage appears and disappears, variables such as RIS phase/mode, STAR-RIS reflection/transmission ratio, and antenna port switching must respond. At this point, strategies such as successive convex approximation (SCA), alternating optimization (AO), sparse updating, or state-triggered control may be used to strike a balance between performance and overhead. Entering the medium-slow time scale, the optimization variables shift to network-level decisions such as UAV trajectories, cooperative-cluster sizes, and node associations. The triggering basis is often hotspot migration, switching of sensing tasks, or environmental evolution trends. Predictive control, reinforcement learning, and hierarchical optimization exhibit advantages at this scale and can realize forward-looking resource orchestration. On the slow time scale, the focus of the system rises to long-term deployment strategies, construction and updating of radio maps, and calibration of digital-twin models. Relying on historical statistical information, scenario reconstruction, and standardized models, global optimization is performed by means such as stochastic geometric analysis, map learning, or offline planning. If all variables are jointly optimized on the same time scale, both computation and control are difficult to bear. Conversely, if sensing results are organized into environmental states with different accuracies and refresh rates and are used to drive hierarchical control, it is more likely to approach the optimum under limited overhead. A multi-time-scale control framework ranging from the millisecond level to the hour/day level can effectively decouple variables with different response speeds, reduce the complexity of joint optimization, and also provide a natural embedding framework for AI-native closed-loop optimization—namely, the mutual coordination between online inference on the fast time scale and offline learning on the slow time scale—offering the prospect of efficient self-evolution for intelligent environment and communication–sensing integrated systems.

There is first top-down constraint propagation among different time scales. Slow-time-scale radio maps and digital twins output regional average path loss, LoS probability, main-scatterer locations, and their prediction uncertainty, thereby providing candidate regions, risk maps, and state priors for medium-time-scale UAV trajectories and cooperative planning. The UAV positions, service-node sets, and user/target association relationships determined on the medium time scale further determine the effective channels, available transmitting nodes, and power budgets for fast-time-scale beamforming, power allocation, and receive filtering. Therefore, medium-time-scale decisions do not directly provide instantaneous beams, but rather specify the feasible domain of the fast-time-scale optimization problem. The corresponding information flow can be summarized as

$$\mathcal{M}_{\text{slow}} \longrightarrow \{\Omega_{\text{mid}}, \mathcal{A}_{\text{mid}}, P_{\text{prior}}\} \longrightarrow \mathcal{F}_{\text{fast}}(\mathbf{q}, \mathbf{A}) \longrightarrow \{\mathbf{W}, \Theta, \mathbf{v}_{\text{rx}}\}, \tag{46}$$

where $\mathcal{M}_{\text{slow}}$ denotes the map or digital-twin state; Ω_{mid} and $\mathcal{A}_{\text{mid}}$ denote the trajectory and association candidate sets, respectively; and $\mathcal{F}_{\text{fast}}$ denotes the fast-time-scale feasible domain determined by upper-layer decisions.

At the same time, fast-time-scale measurements form bottom-up feedback. Beam-misalignment rate, echo residuals, local Fisher information, and link-interruption events can be used to trigger medium-time-scale updates of trajectories or cooperative clusters; state residuals after aggregation over time and space are used to calibrate slow-time-scale radio maps and digital-twin models. Therefore, the interfaces among time scales should transmit low-dimensional states, constraints, and uncertainty, rather than continuously exchanging full-dimensional instantaneous CSI.

The above hierarchical decoupling usually relies on three conditions: the characteristic times of different variables satisfy $T_{\text{fast}} \ll T_{\text{mid}} \ll T_{\text{slow}}$; upper-layer variables remain approximately unchanged within the convergence time of lower-layer algorithms; and the optimal response of the lower layer can be fed back to the upper layer through a low-dimensional value function or statistical quantities. When high-speed vehicle motion, sudden blockage, or rapid changes in task priority make these conditions no longer valid, the system needs to adopt event-triggered cross-time-scale re-optimization, rather than continuing to update variables at each layer independently according to fixed periods.

Table 4 A multi-timescale control perspective on smart-environment-enhanced ISAC systems

Time scale	Representative variables	Triggering criteria	Suitable methods
Fast timescale	Transmit beam, receive filter, partial power allocation	Instantaneous channel variation, short-term sensing results	Convex optimization, iterative beam design, low-dimensional online update
Medium-fast timescale	RIS phase/mode, STAR-RIS reflection-transmission ratio, port switching	User position change, blockage occurrence and removal	SCA/AO, sparse update, state-triggered control

Time scale	Representative variables	Triggering criteria	Suitable methods
Medium-slow timescale	UAV trajectory, cooperative cluster size, node association	Service hotspot migration, task switching, environmental evolution trend	Predictive control, reinforcement learning, hierarchical optimization
Slow timescale	Long-term deployment, radio map, digital twin model	Historical statistics, scene reconstruction, standardized model calibration	Stochastic geometry analysis, map learning, offline planning

6.2 From CSI-Driven to State-Driven

The rise of smart-environment-enhanced ISAC has also promoted an important paradigm shift: the core driving force of system design is moving gradually from traditional "full-dimensional channel state information (CSI)-driven optimization" toward "low-dimensional environmental-state-driven optimization." In conventional communication systems, accurate end-to-end full-dimensional CSI is usually regarded as a prerequisite for high-quality transmission and control. However, in dynamic communication-and-sensing scenarios empowered by intelligent environments, obtaining real-time, high-precision full-dimensional CSI faces severe challenges: on the one hand, large-scale antenna arrays and massive RIS elements lead to extremely high dimensions of the channel to be estimated, making training overhead often difficult to bear; on the other hand, the frequent reconfiguration caused by rapidly changing blockages, mobile users, and reconfigurable surfaces makes the timeliness of full-dimensional CSI difficult to guarantee, and even if it is obtained, it is very prone to becoming outdated. In contrast, low-dimensional environmental states—such as users' positions and velocities, the spatial distribution of major blockers, the geometric structures of dominant scatterers, the position/orientation and attitude angles of RISs/UAVs, and the blockage states of key links—not only have greatly reduced dimensionality, but can often be obtained directly through the sensing function of the integrated communication-and-sensing system itself, naturally providing the closed-loop advantage of "sensing as state." References [9,10] have shown that using such low-dimensional state information acquired through sensing to directly assist core control decisions such as RIS phase design, transmit beamforming, and UAV trajectory planning can not only significantly reduce channel-training overhead, but also effectively improve the system's robustness to channel-estimation errors and environmental dynamics.

Furthermore, the long-term accumulation and learning of low-dimensional environmental states will open a deeper paradigm upgrade. If environmental states are structurally represented and continuously updated through radio maps or wireless digital twins, the system can further establish the ability to predict environmental evolution laws. At this point, the control strategy of the intelligent environment will move from a passive, responsive "sensing-feedback-adjustment" closed loop toward an active, predictive "learning-inference-preadjustment" closed loop: based on historical state sequences, the system can predict the appearance and disappearance of blockages, users' mobility intentions, and the migration trends of service hotspots, thereby adjusting RIS phases, UAV hovering points, or antenna ports in advance. This leap from "reactive updating" to "predictive updating" is expected to fundamentally reduce control latency and signaling overhead.

6.3 Intelligent Algorithms and Learning Control

Faced with the high dimensionality, strong coupling, and dynamic randomness of optimization problems in smart-environment-enhanced ISAC systems, traditional optimization methods are gradually revealing limitations in solution efficiency, real-time performance, and scalability. Data-driven learning methods have therefore naturally become important tools for addressing these challenges. At present, studies have begun to explore the deep integration of AI with intelligent environments, federated learning, adaptive AI, and ISAC networks, and have achieved a series of preliminary advances [10,11,38,39]. However, it should be particularly emphasized that the core value of intelligent algorithms in this specific scenario should not be narrowly understood as a simple paradigm replacement in which "neural networks directly substitute for traditional optimization solvers." More importantly, learning methods should fully exploit the environmental sensing capability naturally possessed by integrated communication-and-sensing systems, inject real-time sensing results into the learning loop as continuous feedback signals, and thereby realize sample-efficient, constraint-controllable, and interpretable online decision-making in dynamically changing environments [77]. These three requirements are especially critical for practical system deployment, because although purely black-box end-to-end learning performs well in simulations, it is often lacking when facing data-distribution shifts, generalization to unseen scenarios, and security-boundary guarantees.

predictable behavioral guarantees. Therefore, for practically deployed intelligent-environment-enhanced ISAC systems, a more promising research path in the future is likely not to pursue completely black-box end-to-end neural networks, but rather to develop hybrid methods that organically integrate physical models, stochastic geometric analysis, graph-structured representations, reinforcement learning, and other methodologies.

7 Application Scenarios and System Value

Starting from the three dimensions of scenario constraints, core bottlenecks, and value focus, this section analyzes five typical scenarios: Internet of Vehicles and intelligent transportation, industrial sites and low-altitude manufacturing spaces, indoor intelligent spaces and ubiquitous services, integrated air–space–ground and wide-area collaborative sensing, and edge intelligence and task-oriented services. These scenarios differ significantly in mobility intensity, environmental geometric complexity, reliability and latency requirements, sensing-accuracy demands, and deployable infrastructure. Consequently, the role played by intelligent-environment-enhanced ISAC also evolves hierarchically from "link compensator," to "environment enabler," and then to "task-intelligence engine."

7.1 Internet of Vehicles and Intelligent Transportation

The Internet of Vehicles is one of the most representative application scenarios for intelligent-environment-enhanced ISAC. High-speed mobility, severe blockage, disparities between in-vehicle and out-of-vehicle links, and positioning-accuracy requirements all expose clear shortcomings in traditional communication systems and conventional vehicle-mounted sensors. Vehicle-mounted STAR-RIS can simultaneously enhance externally perceptible echoes and internally received terminal signals, realizing the dual optimization of "externally visible and internally reachable" [^9]; fixed roadside surfaces can be used for blind-zone compensation and intersection coverage expansion; and multi-roadside-unit collaboration further supports continuous positioning, road-segment-level environmental sensing, and cooperative scheduling. More importantly, vehicle trajectories in transportation scenarios exhibit relatively strong regularity, which makes perception-based predictive control and multi-vehicle collaborative environmental control highly feasible.

7.2 Industrial Sites and Low-Altitude Manufacturing Spaces

Industrial scenarios often involve complex metallic reflections, numerous obstacles, stringent reliability requirements, and low-latency demands. For such scenarios, the intelligent environment is not only an auxiliary means of improving communication coverage, but also a key infrastructure for enhancing environmental perceptibility and production-process observability. Fixed RIS can be used to penetrate shadowed regions caused by complex factory layouts; hybrid surfaces can locally perform lightweight state monitoring; and multi-base-station collaboration can enable more robust tracking and control of key equipment and mobile robots. For low-altitude industrial or warehouse UAV systems, the UAV platform itself can simultaneously undertake communication relaying, aerial sensing, and local environmental reconstruction tasks.

7.3 Indoor Intelligent Spaces and Ubiquitous Services

Indoor spaces such as offices, shopping malls, hospitals, and homes are important deployment scenarios for the integration of low-power intelligent metasurfaces with Wi-Fi / cellular ISAC. Compared with outdoor scenarios, indoor spaces have the advantage of relatively stable geometric structures, making them suitable for the deployment of long-term effective radio maps, digital-twin models, and low-frequency-updated surface-control strategies. The value of the intelligent environment in such scenarios lies not only in improving downlink throughput, but also in supporting device-free human-activity recognition, indoor positioning, security sensing, and space-utilization analysis. As sensing-privacy issues become increasingly prominent, wireless-based non-imaging sensing and its combination with environmental control may become an important technical route for indoor intelligent spaces.

7.4 Integrated Air-Space-Ground and Wide-Area Collaborative Sensing

For tasks such as wide-area coverage, low-altitude economy, ocean monitoring, and emergency communications, a single ground infrastructure often struggles to simultaneously meet the requirements of communication reachability and sensing continuity. Integrated air–ground networks, low-orbit satellites, and high-altitude platforms can provide greater spatial coverage and viewpoint diversity[^10,^11]. If further combined with ground RIS and multi-base-station collaboration, it becomes possible to construct a hierarchical system ranging from local high-precision sensing to wide-area coarse-grained monitoring. It should be noted that, in wide-area scenarios, the core issue is no longer merely the instantaneous performance of a particular link, but rather coordination and division of labor among different nodes, at different altitudes, and with different sensing accuracies.

7.5 Edge Intelligence and Task-Oriented Services

As wireless networks gradually shift from "bit transmission" to "task completion," intelligent environment-enhanced ISAC has also begun to become deeply coupled with edge AI and task-oriented resource scheduling[^38,^39,^78]. In many applications, what the system truly cares about is not the instantaneous rate at a given moment, but whether target recognition is accurate, cooperative control is stable, path planning is timely, and risk warning is reliable. This means that future environmental control should be designed more around task effectiveness rather than a single physical-layer metric. This paper argues that this will be a key step for the field to move from "performance enhancement" toward "system intelligence."

8 Key Issues and Development Trends

On the basis of the preceding discussion, which proceeded step by step from link mechanisms to network collaboration, this section further distills several structural challenges faced by intelligent environment-enhanced ISAC in moving toward practical deployment, and, accordingly, looks ahead to research directions worthy of focused breakthroughs in the future.

8.1 Key Issues

8.1.1 Insufficient Channel and Environment Modeling Although device models and local channel models for RISs, UAVs, and fluid antennas are already relatively rich, what intelligent environment-enhanced ISAC truly needs is a unified dynamic environmental model: it must characterize the motion of users/scatterers, as well as the joint effects of controllable surfaces, array geometry, and multi-node collaboration on the propagation and observation processes. Especially under near-field, wideband, and multi-site cooperation conditions, the conventional assumptions of narrowband far field, independent scattering, and static background are clearly insufficient. In recent years, standardization and channel-modeling studies have begun to incorporate ISAC-specific target channels, background channels, and environmental objects into a unified framework[^79], but there remains a gap before such models can directly support complex closed-loop control of intelligent environments.

8.1.2 Communication and Sensing Objectives Are Not Always Aligned An easily overlooked but extremely critical issue is that the configuration that is optimal for communication in an intelligent environment is not necessarily optimal for sensing, and vice versa. Communication tends to prefer multi-user decorrelation, low interference, and stable high gain; sensing tends to prefer high observability, diverse geometry, separable parameters, and, on some links, even requires larger observation structures[^8]. In network-level systems, this contradiction is further manifested in cluster size, waveform correlation, interference cancellation, and topology deployment[^11,^13]. Therefore, future research needs to upgrade from "trade-offs under shared resources" to "structured coordination under conflicting objectives."

8.1.3 Scalability of Multi-Objective, Multi-Surface, and Multi-Node Systems Single-objective and single-surface scenarios help reveal mechanisms, but practical systems inevitably involve the coexistence of multiple objectives, multiple users, multiple surfaces, and multiple nodes. At this point, echo separation among targets, information cooperation among surfaces, clock synchronization across nodes, fusion of heterogeneous observations, and task-priority scheduling will rapidly become bottlenecks[^8,^11]. In particular, when multiple RISs jointly participate in sensing, how to fuse multi-surface observations from limited echo overhead and how to achieve high-quality joint localization without sharing raw data remain open problems.

8.1.4 Analytical Tools and Architectural Challenges in Network-Level Collaboration Current research on network-level intelligent environment-enhanced ISAC still needs further breakthroughs in the following aspects. First, performance analysis of intelligent-environment networks based on stochastic geometry remains insufficient. Modeling intelligent nodes such as RISs and UAVs as spatial stochastic processes, and analyzing the impact of their density, deployment modes, and configuration strategies on network-level ISAC performance, have so far only seen preliminary attempts and are not yet sufficient to support theoretical guidance for large-scale deployment. Second, hierarchical and clustered network-level control architectures and signaling-exchange protocols are still immature. The multi-layer architectural design of "central controller—cluster head—intelligent metasurface/mobile node," the formulation of clustering rules, and information-exchange mechanisms under limited feedback still require systematic solutions.

8.2 Future Development Trends

8.2.1 AI-Native Closed Loops, Radio Maps, and Digital Twins

One of the trends most worthy of attention in the coming years is the integration of intelligent environment-enhanced ISAC with AI-native network control, radio maps, and digital twins[^38,^39,^80,^81]. Its core idea is not simply to add a learning module to an existing system, but to regard sensing, communication, and environmental control in their entirety as a dynamic state-estimation and task-decision process. Sensing continuously updates the scene state; maps/twins store and predict the environmental structure; and AI determines, according to task requirements, when to update surfaces, when to adjust topology, and when to switch collaborative policies, thereby achieving higher overall effectiveness during long-term operation. The key scientific issues here include: how to compress state representations, how to calibrate long-term models, and how to implement low-power closed-loop decision-making at the edge.

In addition, ISAC naturally has stronger environmental sensing capabilities, but this also implies higher privacy and security risks. The environmental control plane itself may also be subject to attacks such as forged states, deceptive reflections, model poisoning, and control hijacking. Therefore, future research must also simultaneously consider communication confidentiality, sensing privacy, environmental-control reliability, and AI model security.

8.2.2 Task-Oriented and Semantic Environmental Control

Most existing studies focus on physical-layer indicators such as rate, SNR, and CRLB. However, when addressing tasks such as autonomous driving, robot collaboration, and intelligent manufacturing, what the system truly needs to optimize is often decision accuracy, recognition reliability, and control stability. This leads to a direction that deserves further strengthening: environmental control should be oriented toward tasks and semantics, rather than only toward signal power. In other words, the design objectives of RIS phase shifts, UAV trajectories, and array configurations should not merely be to strengthen the received signal, but should make the environmental information most relevant to the current task more observable, make key communication services more reliable, and direct overall system resources toward the most valuable information flows. This perspective is naturally converging with edge intelligence, semantic communication, and value-driven sensing.

8.2.3 Theoretical Tools and Optimization Methods for Network-Level Intelligent Environments

For large-scale heterogeneous intelligent-environment deployment, the future requires the development of theoretical tools and methodological systems with greater interpretability and operability. At the level of theoretical analysis, stochastic geometry is expected to become a core tool for characterizing the laws between intelligent-node density, spatial distribution, and service performance, providing statistically meaningful performance boundaries for network planning and deployment strategies. At the level of optimization methods, hierarchical and cluster-based optimization is expected to decompose global network problems into subproblems with tight intra-cluster coupling and loose inter-cluster coupling, approaching the global optimum at an acceptable computational cost. Meanwhile, hybrid learning–optimization methods based on graph neural networks for relationship modeling and using sensing results as warm-start signals will also provide new solution paths for high-dimensional coupled problems. At the level of security design, security and privacy should be incorporated into the optimization framework as endogenous constraints from the very beginning of architectural design. The synergistic evolution of these theoretical tools and methodologies will promote intelligent-environment-enhanced ISAC from single-point validation toward network-level deployable solutions, and will also lay the foundation for future standardization and real-field measurement.

9 Conclusion

The integration of intelligent environments with communication and sensing marks the transition of wireless systems from "node-centric transmission networks" to "environment-centric collaborative intelligent systems." From fixedly deployed RIS to vehicle-mounted surfaces, from UAV topology reconstruction to fluid antenna geometry adaptation, and then to multi-base-station collaborative communication and sensing networks, existing research has clearly shown that the propagation environment can become an optimizable resource as important as spectrum, power, and time. ISAC provides the necessary sensing capability for low-overhead, closed-loop, task-relevant control of this resource. On the basis of representative literature in this field, this paper has systematically reviewed the concepts, architectures, mechanisms, metrics, and challenges in this direction, and further emphasized several core understandings: first, the key to environmental control is not merely gain enhancement, but the reshaping of channel rank, correlation, and observation geometry; second, the optimal requirements of communication and sensing for the environment are not always consistent, and the relationship between the two must be coordinated through structured design; third, truly valuable future systems should realize closed-loop operation across multiple time scales, with low overhead and within task-oriented frameworks.

Overall, intelligent-environment-enhanced ISAC is still in a stage of rapid development, but its research focus is shifting from device feasibility and local performance gains toward network-level collaboration, scalable control, standardized modeling, and verification in real scenarios. With AI-native networks, radio maps, digital twins, 空

With the further development of space-air-ground integrated platforms and task-oriented services, the integration of intelligent environments with communication and sensing is expected to become a key technological foundation for 6G and even later wireless systems.

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Smart Environments and Integrated Sensing and Communication: Opportunities and Challenges from Link Design to Network Cooperation

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Abstract Smart environments and integrated sensing and communication (ISAC) are steering 6G from "signal transmission" toward "collaborative environmental perception and proactive control" . Unlike conventional designs that treat the environment as an external random factor, smart environments leverage programmable metasurfaces, intelligent transmissive and reflective surfaces, vehicle-mounted surfaces, unmanned aerial vehicles (UAVs) and other autonomous platforms, reconfigurable antennas, and multi-base-station cooperative networks to transform propagation paths, array geometries, coverage topologies, and node cooperation into optimizable degrees of freedom. ISAC, through shared waveforms, spectrum, and infrastructure, provides real-time feedback on environmental understanding, target localization, blockage awareness, and state prediction, forming a closed loop where "the environment empowers sensing and communication, and sensing and communication in turn refine the environment" . This paper systematically surveys the conceptual boundaries, core technologies, typical architectures, key gain mechanisms, and network-level cooperation modes of smart environments and ISAC, with emphasis on how fixed surfaces, target-mounted surfaces, hybrid sensing surfaces, UAV platforms, fluid antennas, and multi-base-station cooperative ISAC networks contribute to coverage extension, channel rank reshaping, target resolvability enhancement, multi-static sensing, and sensing-assisted communication. Furthermore, the paper identifies common design issues regarding performance metrics, optimization variables, and closed-loop system operation, and analyzes the intrinsic tensions between high-rank channel demands and line-of-sight (LoS) link preferences, as well as between communication decorrelation requirements and sensing geometric diversity needs. Finally, key challenges in typical scenarios, including vehicle-to-everything (V2X), industrial manufacturing, indoor spaces, and integrated space-air-ground networks, are summarized, along with promising directions for future research.

Keywords Smart environment, integrated sensing and communication, reconfigurable intelligent surface (or intelligent reflecting surface), smart propagation engineering, cooperative ISAC network, reconfigurable antenna

Note: Figure translations are in progress. See original paper for figures.