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# Six Integration Avenues for ISAC in 6G and Beyond

Nuria González-Prelcic, Dario Tagliaferri, Musa Furkan Keskin, Henk Wymeersch, Lingyang Song

**Abstract**—Integrated sensing and communication (ISAC) is a key technology for future Sixth Generation (6G) networks, enabling sensing and communication services by exploiting a single equipment and waveform. This paper introduces six novel integration strategies to enhance ISAC performance and unlock new applications, assuming a communication-centric approach. These include integrating multiple network elements, such as base stations and user devices, to improve sensing accuracy and spatial resolution through coherent and incoherent processing. Multi-band ISAC is also explored, highlighting the advantages of diverse frequency bands for optimized sensing and communication. We also discuss the potential of combining data from multiple network sensing configurations, terrestrial or non-terrestrial, and also including standalone sensors. The integration of data-driven and model-based methodologies is also discussed as an avenue to overcome limitations in the models or the methods exploited in conventional ISAC solutions. Cutting-edge hardware, including intelligent surfaces and metasurface antennas, is examined for its potential to revolutionize ISAC capabilities. Finally, we outline the challenges and future directions in achieving a fully integrated ISAC network, where sensing data drives network operations for enhanced efficiency and autonomy.

**Index Terms**—6G, Beyond 6G, Integrated sensing and communication.

## I. INTRODUCTION

Wireless networks are rapidly evolving to meet the growing demand for seamless communication and environmental awareness. As we move toward 6G, the integration of sensing and communication (ISAC) is becoming a key feature, enabling networks to function as both communication systems and environmental sensors. This dual capability supports a variety of applications, including autonomous driving, smart cities, and industrial automation.

We consider communication-centric ISAC systems, which reuse frequency bands, multiple-input multiple-output (MIMO) architectures, and waveforms from communication for sensing, as discussed in detail in [1], [2]. Specifically, we explore a heterogeneous cellular implementation of the ISAC concept, where various types of users—ranging from smartphones to connected robots and vehicles—and base stations (BSs) in macro, micro, and pico cells can all function as sensing nodes. Additionally, non-terrestrial nodes, including aerial and space segments, may also be part of the ISAC network. The ISAC link can operate across a variety of frequency bands allocated to cellular networks, including Frequency Range 1 (FR1) from 400 MHz to 7 GHz, millimeter wave or Frequency Range 2 (FR2) from 24 to 70 GHz, and upper mid-band or Frequency Range 3 (FR3). The available bandwidths and propagation mechanisms vary

across these frequency bands, leading to different trade-offs between coverage, spectral efficiency, and sensing accuracy.

MIMO technology, already integral to current cellular networks at FR1 and FR2, is expected to play a key role at FR3 as well. However, the diverse MIMO architectures across these bands introduce distinct signal models and constraints that must be addressed to enable seamless sensing and communication. Generally, higher frequency bands provide larger bandwidth and require the use of larger antenna arrays, which enhance both sensing performance and data rates. However, challenges such as blockage management and hardware impairments must be carefully considered.

Regarding waveforms, we assume that orthogonal frequency division multiplexing (OFDM) and its multiple access variant, OFDMA, serve as the foundation for the ISAC cellular system. MIMO-OFDM is particularly well suited for ISAC systems due to its ability to introduce pilot signals in time, frequency, and space, which can be leveraged for both channel and target parameter estimation. Once the receiver extracts the relevant parameters for a specific link, they are fed into the processing chain for sensing, which depends on the network sensing configuration. Specifically, we consider the basic *sensing configurations*<sup>1</sup>—monostatic, bistatic, and multistatic—which are defined here to clarify concepts discussed in subsequent sections.

In *monostatic* ISAC systems, the transmitter (TX) and the sensing receiver (RX) are co-located on the same device and share the same clock for up-conversion and down-conversion, avoiding synchronization issues. Monostatic sensing can be either BS-centric or user equipment (UE)-centric. BS-centric monostatic sensing relies on the echoes of downlink transmissions to detect the targets in *global* coordinates, because the BS is part of the infrastructure with a known location. On the other hand, UE-centric monostatic sensing can be implemented in sidelink or uplink and provide a complementary view of the physical environment in UE-local coordinates. The mapping from local to global coordinates requires the UE to continuously estimate its position and orientation, thus introducing additional errors on targets' location. A challenge with monostatic sensing is that it requires in-band full-

<sup>1</sup>Throughout the text, we make a clear distinction between *sensing modality* and *sensing configuration*. Sensing modality refers to the method or mechanism through which sensors detect and measure attributes of their environment (e.g., via radio frequency (RF) signals, visible light, infrared and inertial measurement units (IMUs)). On the other hand, sensing configuration specifically pertains to the architectural arrangement in which RF sensors operate, such as monostatic, bistatic or multistatic setups. These configurations describe the relative positions and interactions between the transmitter, receiver and targets within both terrestrial networks (TN) and non-terrestrial networks (NTN).

duplex operation and sufficient isolation between the TX and the sensing RX to avoid self-interference. In *bistatic* ISAC systems, the TX and sensing RX are located on separate devices, and their mutual distance can be comparable or even larger than the distance with the targets. Bistatic sensing can take place with different configurations such as BS-to-BS, BS-to-UE, UE-to-BS, and UE-to-UE, exploiting downlink, uplink, and sidelink connections. In bistatic sensing, the UE positions may be unknown, and TX and RX do not share the same clock. Maintaining accurate synchronization as well as relative positioning poses a major challenge for bistatic sensing. Moreover, unlike monostatic sensing, the TX signal data may not be available at the sensing RX, resulting in loss of signal-to-noise (SNR) and additional processing complexity. Finally, *multistatic* sensing involves multiple TXs and RXs operating in both monostatic and bistatic fashion, offering improved sensing performance (coverage, spatial resolution and localization accuracy [3]) at the price of a significant synchronization burden.

While ISAC has been addressed extensively in the technical literature (see for example the tutorials in [1], [2]), most of the advances in communication-centric ISAC have focused on developing the techniques to enable the sensing capability of a single TX-RX link. Moreover, the considered system models and configurations are often oversimplified, assuming single-band operation, neglecting channel parameter estimation errors, and overlooking hardware impairments such as clock offsets, antenna array offsets, calibration errors, etc. Evaluations are frequently conducted using simplistic and synthetic simulation scenarios, yielding performance metrics that are unlikely to be achievable in practical implementations. In this paper, we argue that additional integration avenues, still in their early stages, can significantly enhance ISAC's dual performance in practical scenarios or enable new applications. These integration strategies include the *coordination of multiple network elements*, i.e. integrating information from multiple sensing nodes, to achieve performances that surpass those obtained from single-link parameters; the use of *multi-band communication* for sensing, i.e. integration of spectrum, which can further enhance performance in practical settings that operate simultaneously across several subbands (for example for subcarrier aggregation); the combination of *different sensing configurations*, i.e. integrating sensing information from monostatic and bistatic measurements, or network sensing and standalone sensors; the balancing of *model- and data-driven solutions* to tackle deficits of the models being exploited, limitations of the algorithms, and lack of real data for realistic simulation; the *operation with advanced hardware*, to integrate new developments in circuit / antenna design into the techniques to perform network sensing, which in prior work mainly assume the utilization of uniform linear or planar arrays; and finally the overall *integration of sensing, communication, and network operation*, by leveraging the sensing information to improve one or more aspects of the network itself, including link configuration, link adaptation or network autonomy.

By exploring these six innovative integration avenues depicted in Fig. 1, this paper presents a forward-looking vision

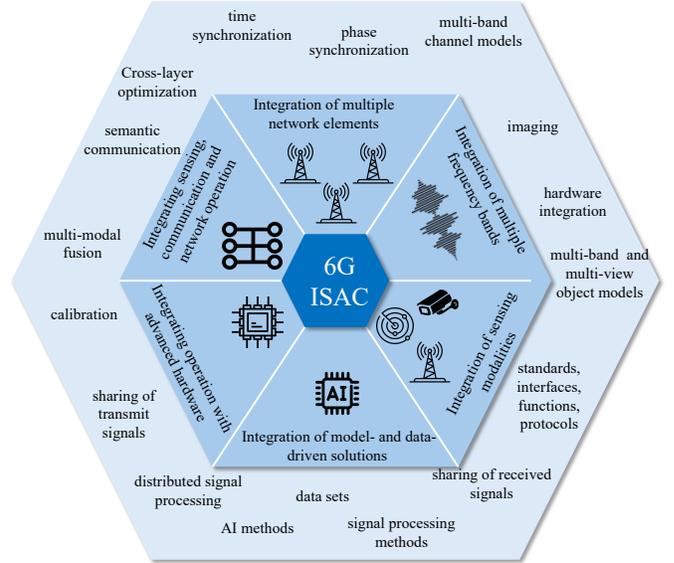


Fig. 1. This paper highlights six integration strategies for next-generation ISAC. The middle hexagon visualizes the strategies, while the outer hexagon shows future research directions.

for ISAC, highlighting opportunities for enhanced performance and practical implementations in 6G and beyond. By expanding on these foundations and proposing novel integration approaches, we aim to contribute a fresh perspective to the field, offering actionable insights for the design and deployment of next-generation ISAC systems.

The rest of the paper is structured into several key sections. Section II discusses the coordination of various sensing nodes, including base stations, user equipment, and non-terrestrial infrastructure, to enhance sensing and communication performance. Section III explores the use of different frequency bands to improve performance and adaptation to practical settings, detailing the benefits and trade-offs of operating in different frequency bands to be exploited in future cellular systems. Section IV examines the fusion of monostatic, bistatic, and multistatic sensing techniques, as well as integrating network sensing with external sensors for a more comprehensive environmental understanding. Section V investigates the balance between leveraging traditional signal processing models and employing AI-driven approaches to address ISAC challenges, including method limitations and model uncertainties. Section VI focuses on the integration of cutting-edge hardware technologies, such as reconfigurable intelligent surfaces (RIS), fluid antenna systems, and holographic surfaces, to enhance ISAC capabilities. Section VII discusses how sensing information can be used to optimize network operations, including channel prediction, beam management, and proactive blockage mitigation. Finally, Section VIII concludes the paper summarizing the proposed strategies, emphasizing the opportunities and challenges.

## II. STRATEGY 1 – INTEGRATION OF MULTIPLE NETWORK ELEMENTS

Recent research has focused on the design of single ISAC nodes, balancing communication metrics with sensing metrics.

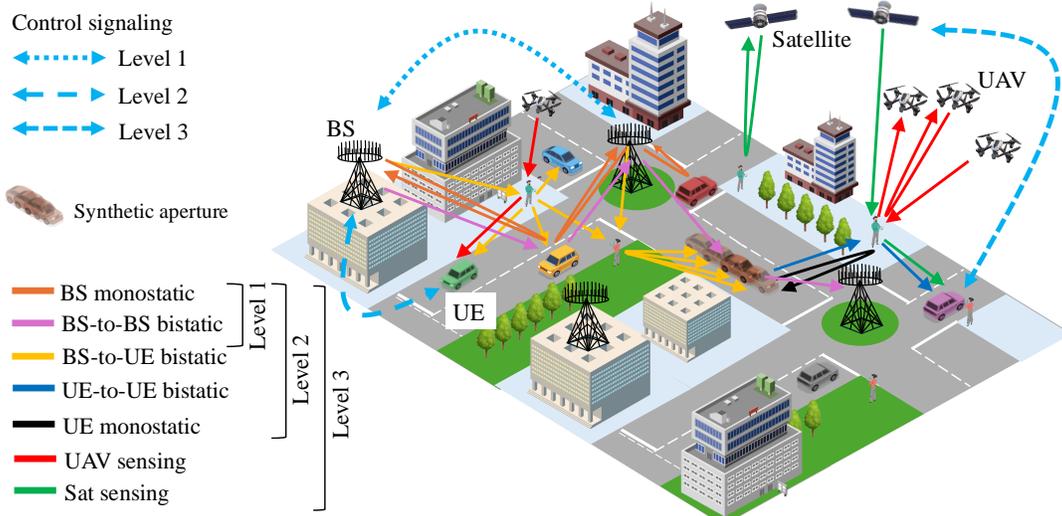


Fig. 2. The three levels of spatial integration. Level 1 (Section II-A) integrates monostatic and bistatic measurements from multiple BSs. Level 2 (Section II-B) integrates monostatic and bistatic measurements from multiple UEs and BSs. Level 3 (Section II-C) adds the measurements from new infrastructure technologies (UAVs, HAPS, satellites, and others).

However, the performance of these nodes is limited by factors such as TX power, carrier frequency, bandwidth, and number of antennas, which are constrained by regulations and cost. The potential of wireless communication networks to serve as a distributed and ubiquitous sensor system offers vast, largely unexplored possibilities, where both infrastructure and user equipments can function as TX and RX units. From a sensing perspective, the integration of multiple network nodes requires appropriate coordination, whether in centralized ISAC networks or cooperative ones. This raises several key questions that we discuss next.

The first question relates to identifying the appropriate key performance indicators (KPIs) for the desired sensing outcome. For example, localization involves estimating target parameters (e.g. position, velocity) with maximum accuracy, typically measured by mean squared error (MSE), while imaging focuses on creating 2D or 3D maps of the complex reflectivity of the environment, where spatial resolution is the key metric [4]. The second question concerns the potential benefits of network-level sensing. Although ubiquitous high-resolution sensing might serve as a standalone service, integration with communication should ideally enhance overall system performance. The third aspect is the level of integration, deciding which types of device to coordinate—whether infrastructure elements, UEs, and others—and sensing configurations to fuse—monostatic, bistatic or both—as well as determining the scale at which this integration is feasible, considering costs such as synchronization. This decision influences the data fusion approach, that is discussed in detail in Section IV. Lastly, an important aspect is related to the required information exchange among ISAC nodes to enable integration, namely the specific type of data to share and the consequent signaling overhead. In the following, we discuss three promising strategies for the integration of multiple network elements, hereafter referred to as spatial integration levels, in cascaded order of potential benefits and related complexity, as illustrated

in Fig. 2.

#### A. Integration of Multiple Infrastructure Elements

Integrating multiple base stations (BSs) allows for a multi-perspective view of the environment, improving sensing performance and reliability by reducing the impact of potential occlusions. *Incoherent* data processing from multiple BSs can be achieved by mutually exchanging either local estimates (such as targets' position, velocity, etc.) or directly baseband data (without carrier phase information). This requires coordinating time, frequency, and space resources to avoid interference and minimize the impact on communication services. In this setup, the integrated SNR scales with the number of co-operating BSs, but the spatial resolution is constrained by the available bandwidth and the aperture of a single BS. *Coherent* data processing, instead, retains the carrier phase information, allowing a significant improvement in spatial resolution (from many wavelengths to sub-wavelength) by treating the BSs as a *distributed* phase-coherent sensor. In this case, the network of BSs is equivalent to a sparse antenna array, whose elements are distributed in space and create an aperture much larger than the single BS alone, allowing for a spatial resolution limited only to half of the carrier wavelength. However, distributed coherent sensing presents significant challenges. First, phase-coherent operation of multiple ISAC BSs implies that they must be tightly synchronized in time, frequency, and phase, so that the network must predict the time of flight (TOF) to and from the targets with an accuracy dictated by the carrier frequency [5]. In addition, the relative BS-to-BS positions must be known (in bistatic settings) within a small fraction of the carrier wavelength to avoid bias in the TOF. These requirements far exceed the conventional clock alignment and positioning standards for incoherent fusion, dictated by bandwidth. Notice that no available technology (such as disciplined oscillators) allows to meet the coherent synchronization requirements for

carrier frequencies larger than 10 GHz.<sup>2</sup> Second, phase coherence can only be harnessed for targets that exhibit *angular coherence*, meaning a complex reflection coefficient invariant in space (across all ISAC nodes involved). The latter aspect is fundamental in remote sensing, but it has not been investigated in detail for communication systems. Third, ensuring that the network operates as a single distributed device requires tight coordination at the physical level, carefully managing time, frequency, and space resources to maximize performance and minimize interference. The joint allocation of resources across multiple BSs requires the exchange of additional contextual information regarding the environment in which the individual BSs operate. For infrastructure elements, this information exchange maps into a control overhead on the fronthaul and backhaul BS-to-BS links used for communication. Indeed, the control overhead might be the effective bottleneck for the distributed sensing approach, limiting its practical scalability. In this sense, artificial intelligence (AI) and the recent advances on semantic communications may be the keys to limit the control overhead and unlock the potential of distributed sensing at the infrastructure.

### B. Integration of Multiple User Equipments

An advanced step in integration involves leveraging the new sensing capabilities offered by UEs. These ubiquitous connected users can contribute additional sensing measurements, either with the infrastructure through downlink / uplink signals or with other devices via device-to-device (sidelink) connections [6]. Fig. 3(a) illustrates the particular case of a collaborative positioning system in the context of vehicular networks, where the connected vehicles are scheduled in groups to be jointly localized [7]. In this case, the vehicle/s with a line-of-sight (LOS) vehicle-to-infrastructure (V2I) link acts as an anchor/s for the other vehicles without LOS (targets). The V2I and vehicle-to-vehicle (V2V) links are exploited to provide measurements to jointly estimate the position and orientation of the target vehicles. Note that the system has to account for different clock offsets between the elements in the group as well as different array orientations. The simulation results in Fig. 3(b) show the performance enhancement that can be achieved by collaborative geometric localization (V2V + V2I) versus individual geometric localization of the different target vehicles when only a non-line-of-sight (NLOS) V2I can be exploited.

In addition, mobile users, such as connected and automated vehicles (CAVs), can use their motion to create wide synthetic apertures in monostatic and bistatic settings, by leveraging the V2I and V2V links. This approach enables high-resolution sensing even with low-cost off-the-shelf devices and under limited bandwidth conditions [8]. With such a density of measurements in space, the network can achieve a nearly complete environmental view at centimeter-level resolution

<sup>2</sup>Besides the phase synchronization challenges of different BSs, the geometric calibration of BS positions on the carrier wavelength scale is nearly impossible at those frequencies, requiring to know the relative position of BS array's phase center with a millimeter-level accuracy, at typical BS-to-BS distances of hundreds of meters.

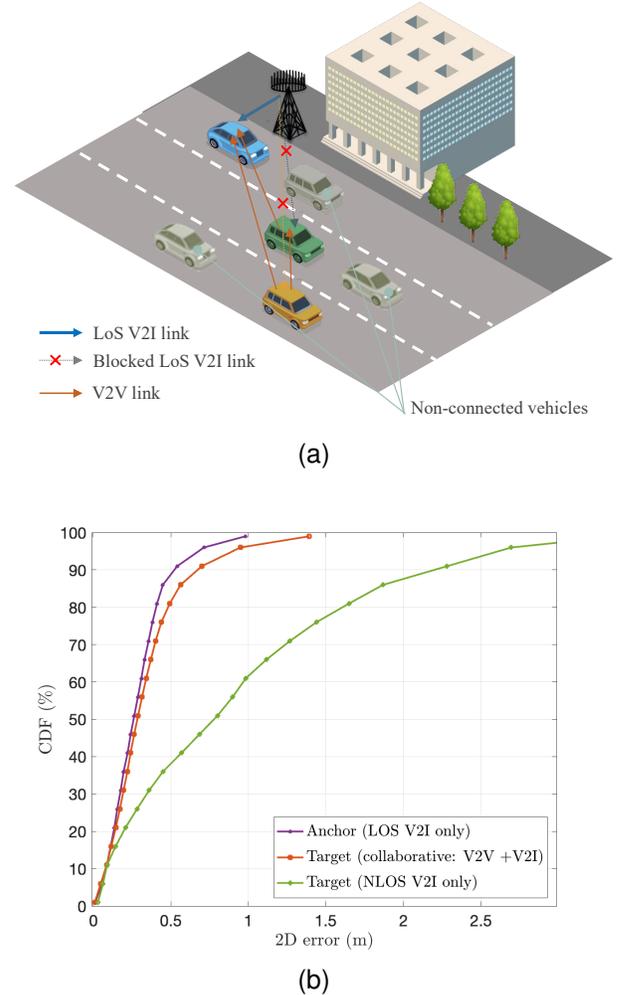


Fig. 3. Positioning results for the vehicular setting in Fig. 3(a), showing the performance for the vehicles in NLOS conditions (targets) when collaboratively localized (red line) versus the independent positioning results exploiting a NLOS V2I link (green line); the vehicle that acts as anchor is in LOS with the BS and can be accurately localized by only exploiting the V2I link (purple line).

through coherent processing of various heterogeneous measurements. However, the previously discussed synchronization and positioning requirements become stricter when applied to this broader set of diverse nodes. Given the mobility of user devices, the relative positions of TX and RX in bistatic settings must be continuously estimated and updated, requiring significant signaling and computational burden. In fact, for coherent fusion, the required level of temporal *and* spatial synchronization cannot be achieved with any of the existing technologies, so data-driven *phase calibration* approaches can be exploited to fully harness phase coherence and achieve maximum sensing performance [5]. Moreover, the inclusion of mobile devices in a distributed and cooperative ISAC network poses the practical problem of energy consumption. On one side, any control overhead comes with a non-negligible energy cost, and, as far as battery-powered devices are concerned, most of energy is drained by intensive computing tasks. Therefore, efficient distributed ISAC strategies shall aim at minimizing the overall computational complexity and energy

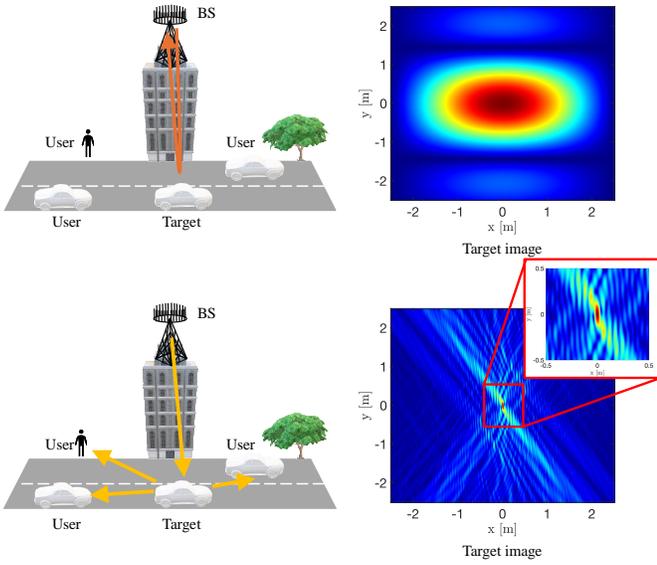


Fig. 4. SAF for progressive integration levels and coherent processing. The top figures show the SAF obtained with a single monostatic BS measurement. The bottom figures showcase the result obtained with multiple bistatic BS-to-UE measurements.

consumption. To showcase the potential of phase-coherent joint processing of multiple ISAC nodes, Fig. 4 shows two examples of the coherent spatial ambiguity function (SAF), namely the image of a point target, obtained with: (i) a single monostatic BS measurement (top figure) and (ii) multiple BS-to-UE bistatic measurements (bottom figure). Integrating a large number of measurements from multiple UEs allows shifting from tens of centimeters of spatial resolution down to a few centimeters, provided that suitable resource allocation and phase calibration is applied.

### C. Integration Goes 3D: Sensing with New Infrastructure Elements

The upper level of spatial integration involves incorporating NTN, supported by unmanned aerial vehicles (UAVs), high-altitude platforms (HAPs) and satellites—Low Earth Orbit (LEO), Medium Earth Orbit (MEO), and Geostationary Orbit (GEO)—into the infrastructure. Each of these comes with different characteristics and challenges, that yield a plethora of new opportunities. NTNs, due to their altitude and continuous coverage, can serve as invaluable components for precise positioning and environmental sensing, especially in areas where TNs either do not exist or are not reliable [9]. This integration marks a shift from 2D to 3D networks, with the aim of providing reliable high-speed communication services in areas poorly covered. A key advantage of NTNs is their mobility, with elements such as UAVs capable of dynamically forming *ad-hoc* cooperative swarms to fulfill ISAC goals. In this setting, the sensing capabilities extend to ultra-high-resolution 3D sensing, shifting from localizing targets in a 2D space to generating high-fidelity digital twins of the environment. Furthermore, an intriguing possibility is the investigation of the internal structure of selected objects

by *tomographic* processing of data acquired in low frequency bands below 10 GHz (e.g., 3GPP FR1 for terrestrial networks and S-band for NTN), where penetration of EM waves into obstacles is significant. These capabilities offer significant benefits across various ISAC applications, including safety-critical and forensic uses. However, this high level of integration demands tight coordination, exacerbating the challenges related to synchronization, resource allocation and computational complexity. Moreover, the fusion of measurements from NTNs and TNs poses unprecedented challenges, discussed in detail in Section IV-A. Future ISAC systems supporting this full 3D integration of devices shall be designed to strike a balance between performance and cost, with an imperative look at energy consumption.

## III. STRATEGY 2 – INTEGRATION OF MULTIPLE FREQUENCY BANDS

The concept of ISAC in future networks extends beyond utilizing a single frequency band across multiple infrastructure or user device elements for joint operations. A promising approach involves *multi-band* ISAC, which leverages different frequency bands to achieve enhanced sensing and communication functionalities [10]. This enhancement is achieved by harnessing the fact that distinct frequency bands interact differently with the physical environment and provide complementary characteristics for sensing.

Multi-band ISAC can involve coherent or non-coherent approaches, depending on the target properties and operational goals. Synchronization again plays a critical role—coherent approaches require tight synchronization across frequency bands to maintain phase relationships, while non-coherent approaches can tolerate independent processing of each band, offering more flexibility at the cost of reduced resolution. Thus, there is a symmetry between multi-band ISAC (considering spectrally separated resources) and ISAC with multiple network elements (considering spatially separated resources), leading to similar considerations in terms of resolution and ambiguities [5].

We distinguish between different types of multi-band ISAC: *inter-band* ISAC, which operates across different ranges, and *intra-band* ISAC, which operates across disjoint sets of subcarriers within one frequency range, mainly to meet interference and spectral emission requirements and to support flexible carrier aggregation.

### A. The Multi-Band ISAC Channel

The channel properties differ significantly across frequency bands, namely FR1 (below 7 GHz), Frequency Range 2 (FR2, spanning 24 to 70 GHz), the upper mid-band (sometimes referred to as FR3 or FR1.2, from 7 to 24 GHz), and sub-terahertz (sub-THz) bands (100-300 GHz). Understanding the differences in these channels, illustrated in Fig. 5, is fundamental to designing effective multi-band ISAC systems. The differences between various bands thus relate how the channel paths interact with various materials, as well as the bandwidth and array sizes used.

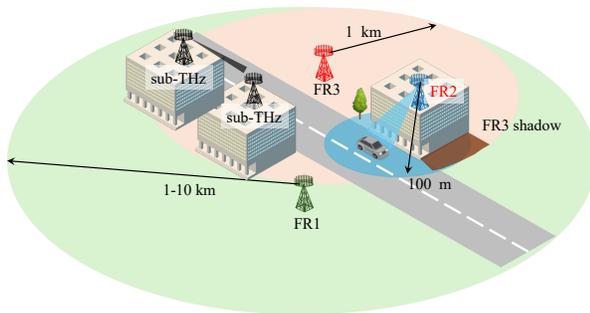


Fig. 5. Sensing when considering different frequency bands in multi-band ISAC, each leading to different interactions with the sensed environment. XXX Henk - should we extend the caption a bit with a few words for each band?

- In FR1, the propagation features facilitate large coverage areas. The signal at FR1 can penetrate most obstacles, making it suitable for applications requiring through-the-wall sensing and tomography. The small Doppler frequencies provide high mobility support, enabling sensing under extreme velocities. The large wavelength causes most objects to appear relatively smooth, creating strong reflections (including multiple bounces). However, the relatively narrow bandwidth limits the achievable data rate and its sensing resolution, making it challenging to disentangle complex interactions with the environment hidden inside the channel, even with large MIMO arrays.
- FR2 involves communication over millimeter-wave frequencies, which provide wide bandwidths (400 MHz in 5G), offering very high data rates and excellent temporal resolution at the cost of limited coverage and the need of large arrays for directional communication. Obstacle penetration is minimal, with few propagation clusters remaining. Large arrays on the infrastructure and user sides provide significant angular resolution, making FR2 a prime band for sensing (on par with powerful 4D radar systems at slightly higher bands), despite commercial setbacks and limitations due to hardware impairments.
- FR3, sometimes called the "golden band" or upper mid-band offers a middle ground with lower coverage than FR1 but improved data rate and resolution, thanks to potentially larger available bandwidth. Poor obstacle penetration leads to significant shadowing, though there are more reflections and propagation clusters compared to FR2. This makes FR3 suitable for around-the-corner sensing and a capacity boost in urban macrocells, further enabled by its support for extremely large antenna arrays.
- Sub-THz frequencies offer even larger bandwidths than FR2 (on the order of GHz), resulting in exceptional resolution for sensing tasks. However, at such high frequencies, blockage and signal absorption by atmospheric components significantly limit the coverage and require fine beams with accurate beam pointing (e.g., for inter-BS links). This makes sub-THz ISAC more suitable for static line-of-sight applications with high spatial resolution requirements, such as imaging.

The combination and fusion of these bands in multi-band

ISAC allows for a flexible system that can adapt to different propagation conditions, data rate requirements, target types, and other application requirements. From a communication perspective, multi-band operation presents challenges such as link configuration across different bands and the need for precise time and frequency synchronization of measurements taken at diverse frequencies. Coherent fusion of multi-band measurements for sensing, however, tolerates significantly smaller synchronization errors compared to communication. Channel parameter estimation or prediction across bands is also essential in multiband operation, both for sensing and communication purposes. However, sensing services demand significantly higher precision in these estimated parameters compared to communication, making this aspect particularly crucial for effective multi-band ISAC deployment.

### B. Inter-band Sensing

Inter-band sensing in the context of ISAC refers to the fusion of sensing information from different frequency bands, such as FR1 and FR2. Practical hardware considerations may prevent the use of coherent methods, which require a single local oscillator, even for monostatic sensing, thus limiting inter-band sensing to non-coherent combining across bands taking advantage of the different propagation properties.

Even with separate local oscillators, simultaneous transmission or reception on multiple bands may be challenging, especially for low-cost, power-limited user devices. Hence, a practical approach is active band switching, which enables the system to dynamically change the operating frequency depending on environmental conditions and sensing requirements.

The fusion of information from these bands is non-trivial. For higher bands (upper FR3 and above), the geometric channel information (e.g., angles, delays, Dopplers) or resulting detections (e.g., 3D locations) can be associated across different bands, allowing for non-coherent fusion and the identification of unique paths in each band. The approach requires sophisticated, yet scalable data association methods. For lower bands (FR1 and lower FR3), complex environments are expected to be a limiting factor, requiring a detailed understanding (and thus modeling) of the channel for the same physical environment across different bands. Data-driven AI methods can be helpful in this direction, as can approaches from electromagnetic and physics compliant signal processing.

### C. Intra-band Sensing

Intra-band sensing deals with the division of a broader frequency band into multiple sub-bands and the (preferably) coherent combination of these sub-bands for sensing purposes. This approach can be particularly beneficial for improving resolution, reducing ambiguity, and improving the robustness of the sensing system [10].

One of the key challenges in intra-band sensing is achieving and maintaining phase synchronization across all sub-bands to avoid performance degradation. Even with phase coherence, the selection of sub-bands may differ for communication and sensing, as sensing requires not just high resolution (narrow

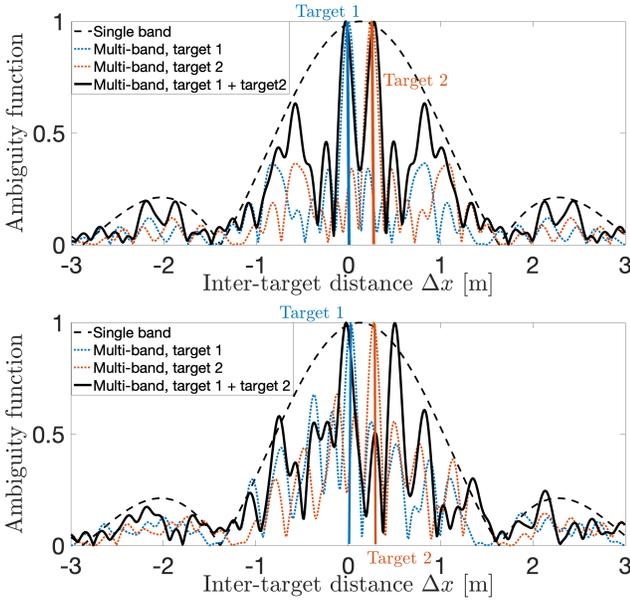


Fig. 6. The ambiguity function of a multi-band vs single-band system, with two closely spaced targets, using 4 bands of 100 MHz, randomly allocated within 1 GHz. The upper one is for perfect phase coherence across the sub-bands, while the lower figure is for a residual error of 20 degrees on the carrier phase on each of the subbands.

main lobe of the ambiguity function) but also controlled ambiguities (low side lobes of the ambiguity function). A careful spread of power across the different sub-bands is crucial to strike a trade-off between these competing objectives. An example of the benefits and challenges in phase-coherent multi-band ISAC is shown in Fig. 6, visualizing the ambiguity function with 2 nearby targets. Phase-coherent operation allows us to resolve the targets, though even minor synchronization errors (20 degrees, or about 5%) cause significant performance degradation. Another challenge relates to modeling for intra-band sensing. The electromagnetic properties of an object may vary across sub-bands, leading to a partially coherent channel. Understanding and modeling these effects are mandatory to fully harness phase coherence and to understand its limitations. The final challenge relates to processing, particularly channel parameter estimation. Sophisticated super-resolution methods are not designed for intra-band sensing and must be revised to account for spectral gaps [11].

#### D. Multi-field Operation

In multi-band ISAC systems, both near-field and far-field sensing must be considered to maximize system flexibility and adaptability [12]. Near-field sensing, which occurs when the distance between the transmitter/receiver and the target is smaller than the Fraunhofer distance, requires different modeling and processing techniques compared to far-field sensing. Since the Fraunhofer distance depends on the wavelength, multi-band ISAC will involve simultaneous near-field and far-field effects, meaning that the same object may be in the near-field for some bands and the far-field for others, while within one band, objects may appear in far-field and near-field. Objects themselves may be treated as point targets or extended

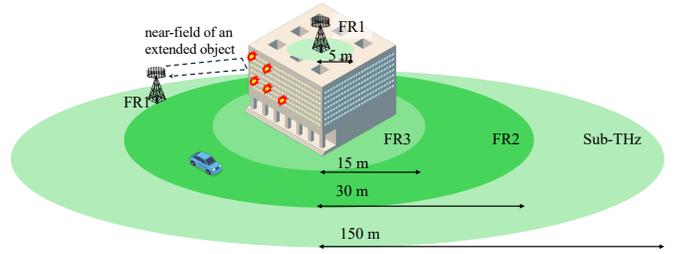


Fig. 7. Near-field and far-field operation at different bands, considering a fixed array size of 0.5 m. Arrays can be in near-field of objects and objects can be in near-field of arrays.

targets, depending on the operating band, so that even at lower bands, BSs may be in the near-field of extended objects.

Near-field ISAC can provide enhanced angular resolution and can even detect the curvature of the wavefront, which is valuable for precise localization and characterization of nearby objects. On the downside, near-field channels are subject to spatial non-stationarity due to varying path loss and obstacles. This makes it challenging to approach the problem from a conventional radar sensing perspective; instead, imaging methods are more suitable. Far-field sensing, on the other hand, is based on plane wave assumptions and is more suitable for scenarios involving large distances between the transmitter/receiver and the target. Modeling and signal processing are less complex, making far-field models a valuable intermediate approximation for some near-field problems. The combination of near-field and far-field sensing, referred to as multi-field operation, allows the ISAC system to dynamically adapt depending on the proximity of the target and the resolution requirements of the task. Another critical aspect of multi-field operation is power optimization across different sub-bands. By jointly optimizing power allocation and band selection, the ISAC system can achieve a favorable trade-off between coverage, resolution, and energy efficiency.

#### IV. STRATEGY 3 – INTEGRATION OF DIVERSE SENSING CONFIGURATIONS AND MODALITIES

The integration of diverse sensing configurations across 6G TN and NTN, along with external sensors (including sensing modalities beyond RF), as depicted in Fig. 8, enables the creation of a more accurate and comprehensive environmental awareness system by capitalizing on the mutually complementary nature of multimodal operation.

Fusion, however, presents several practical challenges including synchronization across different sensing entities, resolving data association, handling data format differences and managing the significant data volumes involved in real-time signal-level fusion (i.e., *tight coupling*). Successfully integrating different configurations and modalities offers benefits like improved localization accuracy in dense urban environments, seamless global coverage in remote regions and support for next-generation applications such as autonomous vehicles, augmented reality and global Internet of Things (IoT) systems.

While Sec. II investigates the integration and coordination of infrastructure elements with a focus on hardware and system-level aspects, this section explores fusion of data from various

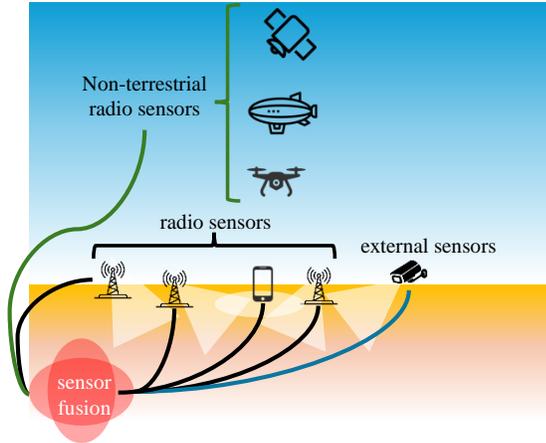


Fig. 8. Fusion of sensing configurations and modalities, including terrestrial and non-terrestrial sensors, as well as external sensors.

sensing configurations and modalities from a lower-level signal processing perspective. We will first consider 6G sensors, and discuss fusion within different configurations. Then, we will describe external sensors and opportunities for fusion with these types of sensors.

#### A. Fusion of Different Network Sensing Configurations

6G systems are expected to employ various sensing configurations, i.e., monostatic, bistatic and multistatic. These configurations offer distinct trade-offs between coverage, resolution and synchronization complexity, can be realized in uplink, downlink or sidelink, and fused at different levels and subconfigurations.

1) *Fusion Levels*: The fusion of radio sensing data occurs at different *levels* that can be functionally split into: (i) *signal-level fusion* (raw in-phase and quadrature (IQ) sample fusion), where multiple IQ data streams collected at different RXs (regardless of the specific configuration) are jointly processed, and (ii) *feature-level fusion*, where different ISAC nodes mutually share locally processed data or directly extracted features (such as targets' position, velocity, orientation and others). Signal-level fusion represents the most challenging approach, requiring multiple TXs and RXs to be mutually calibrated in space and synchronous in time to attain the utmost performance, and further divides into incoherent and coherent fusion, following the definition introduced in Sec. II. Feature-level fusion, while generally less optimal in performance, comes with less stringent synchronization requirements and significantly reduces signaling overhead and processing complexity across network nodes. However, it still necessitates some level of time-stamping to ensure that measurements are accurately fused, accounting for the variable timing of events as recorded by different sensors.

2) *Fusion of Monostatic and Bistatic Sensing Configurations*: Concerning the plurality of available sensing configurations, their fusion can take many forms. A first example is the fusion of *monostatic* sensing data from multiple BSs. Feature-level fusion is mostly effective in the reduction of the

probability of occlusion of the direct path from a BS, providing a robust localization service. Signal-level fusion yields remarkable benefits in terms of localization accuracy, as a consequence of improved SNR and resolution. As discussed in Sec. II, phase-coherent processing across multiple BSs allows improving the spatial resolution by orders of magnitude, but requires tight synchronization and phase-coherent targets. With only monostatic acquisitions, moreover, coherent approaches yield a spatially sparse distributed antenna array, since BSs are usually spaced by tens or hundreds of meters. In this case, there are two major consequences: (i) the inter-BS distance is often comparable or larger than the distance with the targets of interest, leading to a *near-field* operating condition that imposes rethinking the conventional signal processing; (ii) the angular response of such a large array (the *spatial ambiguity function*) is characterized by high sidelobes due to the non-uniform spatial sampling, hindering the practical resolution capabilities.

The issue of high sidelobes can be mitigated by including bistatic BS-to-BS, BS-to-UE and UE-to-BS data, as well as UE-centric monostatic measurements, thus using a *multistatic* sensing system. According to diffraction tomography theory, which rules the resolution and sidelobe level for any sensor geometry, the use of bistatic measurements adds new spatial degrees of freedom and is equivalent to observing the targets with *different spatial frequencies*, revealing physical properties unavailable through monostatic acquisitions only [4]<sup>3</sup>. Fig. 9 shows an example of fusion of monostatic and bistatic acquisitions in a vehicular ISAC network. Five platooning vehicles cooperate to improve the image resolution of two closely spaced targets, where the capabilities of a single vehicle are insufficient. The coherent fusion of monostatic measurements (leftmost figures) improves overall resolution but yields non-negligible sidelobes in the image, making it difficult to detect the targets. In contrast, the coherent fusion of multistatic data (rightmost figures) yields the best result, with clearly distinguishable spots. As can be seen in the upper part of Fig. 9, bistatic acquisitions allow populating the spectral coverage with new measurements.

3) *Fusion with Non-Terrestrial Networks*: The fusion of TN and NTN data creates a robust sensing system, particularly in challenging environments such as rural areas where BSs are sparsely deployed. For instance, in scenarios where TNs provide localized, small-area sensing coverage, inputs from a LEO satellite based NTN localization system can augment the network by providing wide-area or global perspectives [9]. This allows for detection and tracking of targets over much broader spatial domains, making it ideal for applications like maritime surveillance, global transportation tracking or disaster management. However, combining data from TNs and NTNs poses several challenges, including differences in

<sup>3</sup>Diffraction tomography theory states that the response of a target to a collection of mono-chromatic electromagnetic waves is proportional to the spatial Fourier transform of its spatial reflectivity function (i.e., the 2D/3D map of its complex reflectivity), sampled in a given set of spatial frequencies (*spectral coverage*). The latter depends on the relative TX-target-RX position and employed frequency and bandwidth. In this view, monostatic and bistatic measurements allow observing different sets of spatial frequencies, resulting in reconstruction of the target shape with a predictable resolution.

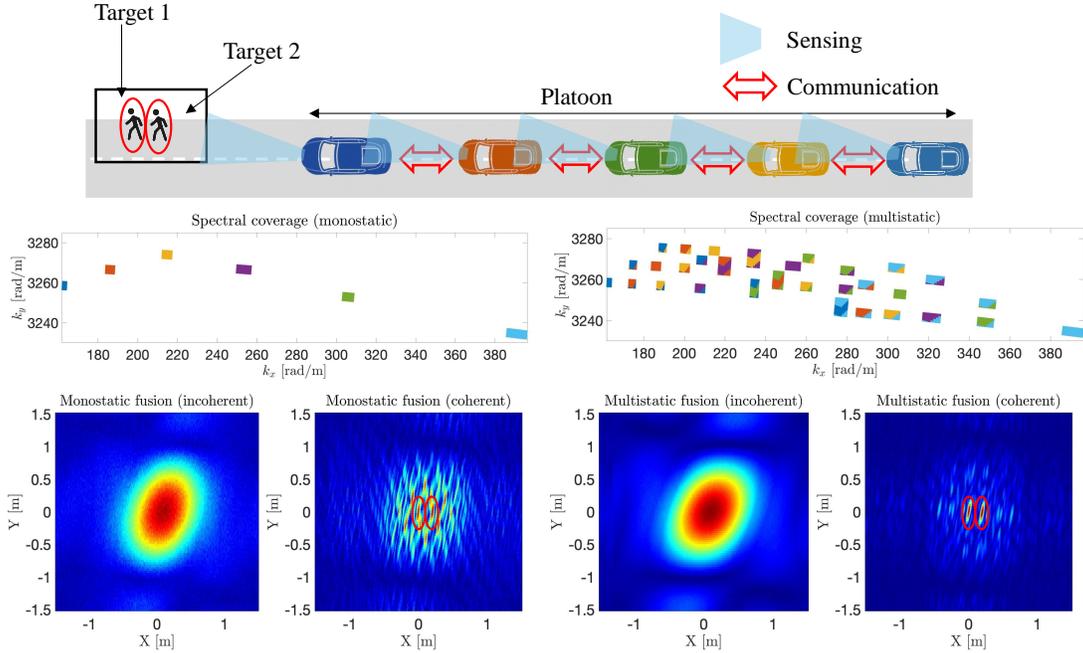


Fig. 9. Incoherent and coherent fusion of monostatic and multistatic sensing configurations for a platoon of radar-equipped cooperating vehicles sensing two close targets (e.g., two pedestrians). By monostatic measurements, the quality of the image is not sufficient to distinguish the two targets due to high sidelobes. This is a consequence of the sparsity of the spectral coverage of the experiment, telling that the equivalent antenna array formed by the vehicles is severely under-sampled in space. Differently, multistatic acquisitions allows filling the spatial spectrum of the image with new measurements, and the image quality improves. Note that although multistatic phase-incoherent fusion does not enhance resolution compared to its monostatic counterpart, it does improve the SNR, as evidenced by a more prominent peak relative to sidelobes.

signal propagation characteristics, significant Doppler shifts and the need for precise mutual synchronization. The inherent delays resulting from long propagation distances in satellite signals and the potential for cross-interference between TN and NTN signals increase the complexity of the fusion process. Moreover, LEO and MEO satellites induce substantial Doppler shifts due to their short orbital periods while GEO satellites, which move synchronously with the Earth, produce minimal Doppler effects. Handling such large Doppler spreads between TN and NTN links requires sophisticated pre- and post-compensation methods at transmit and receive sides. Finally, advanced techniques, such as AI-driven synchronization algorithms, can be employed to ensure real-time fusion across terrestrial and non-terrestrial sensing configurations.

### B. Fusion with External Sensors

Infrastructure nodes and devices will likely be equipped with a variety of conventional sensors. For instance, CAVs use on-board sensors such as Global Positioning System (GPS), camera, lidar, inertial measurement units (IMU), odometer, steering angle sensor and others, yielding position estimates in either global or device-local coordinates. Each of these sensors provide relevant sensing information complementary to 6G network sensing configurations, with associated fusion opportunities.

1) *External Sensor Types:* We break down the external sensors into two categories. First, the sensors that provide absolute information include WiFi, ultra-wideband (UWB), and GPS. In this category, WiFi and UWB are often used for

indoor localization while GPS is more suitable for outdoor localization. By fusing data from these sensors, it becomes possible to deliver seamless, continuous localization coverage across different environments. The second category includes sensors providing relative position information, such as radar, lidar, cameras and IMUs, which can be critical for dynamic environments such as autonomous vehicles. These sensors track nearby objects and obstacles in real-time, and when integrated with absolute positioning systems like GPS, enable highly accurate navigation and situational awareness.

2) *Fusion of Networked Sensing with External Sensors:* Fusion of TN and/or NTN data with external sensors offers significant potential for improving overall robustness in sensing and localization. For example, integrating GPS and IMU data with LEO satellite communication signals enables enhanced localization in urban environments, where GPS signals can often be obstructed, as illustrated in Fig. 10(a). The performance of the GPS+IMU system in a particular trajectory in an urban canyon simulated by ray tracing is shown in the blue curve in Fig. 10(b), while the red line shows the relevant performance gain after GPS correction exploiting a data-driven approach and fusion with IMU data and the estimated direction-of-arrival (DoA) and Doppler frequency of the received LEO satellite communication signal [13]. Another example can be the fusion of UE-centered monostatic sensing with bistatic sensing from BSs and onboard sensors such as radar and lidar. This real-time fusion can be critical for applications such as autonomous systems operating in complex environments. While the fusion with external sensors holds

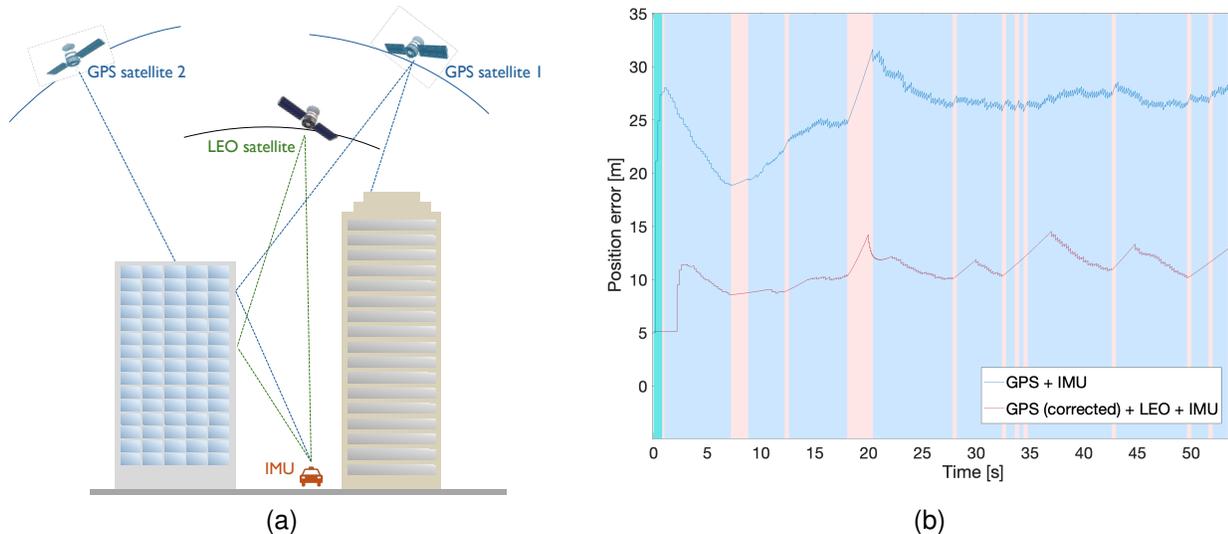


Fig. 10. (a) Illustration of an urban canyon where the GPS signal is either obstructed or experiences the multipath effect, and a LEO satellite communication signal is serving a vehicle on the street, which is equipped also with a GPS receiver and an IMU. (b) Performance gain obtained when fusing IMU, LEO and GPS corrected with a data-driven strategy as in [13]; the introduction of GPS correction and LEO data (one satellite) leads to a reduction of the positioning error of more than 10 m for all the points in the trajectory; the period marked in green, at the beginning of the trajectory, corresponds to a situation where 4 GPS satellites have LoS with the vehicle on the street, before entering the urban canyon, while for the periods marked in blue there are less than 4 GPS satellites in LoS with the vehicle; in the periods in pink, less than 4 GPS satellites are received (not even NLOS components), which explains the abrupt reduction in positioning accuracy.

great promise, several challenges must be addressed. These include differences in data formats, communication protocols, and the need for real-time processing across different sensor types. Achieving seamless integration requires sophisticated AI-driven algorithms capable of managing the alignment and fusion of data streams from these diverse sources without introducing significant latency. Additionally, advancements in edge computing and distributed architectures will play a crucial role in enabling low-latency fusion, ensuring that data is processed and integrated close to the source [14]. Finally, a promising avenue in AI-based integration involves vision-language model-based fusion of images obtained from networked sensing configurations and onboard vehicle sensors [15]. This approach may, however, face challenges in generating accurate textual descriptions of radar images using language models.

## V. STRATEGY 4 – INTEGRATION OF MODEL- AND DATA-DRIVEN SOLUTIONS

Different research communities have approached the problems associated to integrating sensing and communication either from a completely mathematical perspective, exploiting signal processing and optimization, or from a purely data-driven AI approach, which sometimes relies on oversimplified scenarios or too specific settings. In this section, we discuss the challenges associated to new ISAC designs that exploit both well established models and learning strategies, leveraging the strengths of each approach to enhance sensing and communication performance.

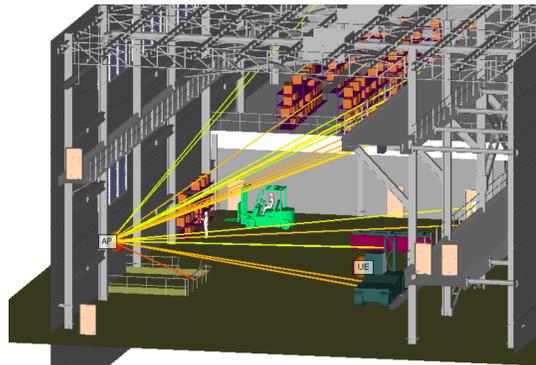


Fig. 11. Ray tracing simulation of a smart factory environment created with Wireless Insite, where the different multipath components exploited for sensing are generated by an electromagnetic simulation. In this case, a monostatic sensing setting was simulated, where the access point (AP) is equipped with a full duplex circuit. The image shows the rays between the TX and RX sides of the AP.

### A. Datasets for ISAC

A key enabler for the development of relevant machine learning solutions for ISAC is the availability of high quality and trustworthy labeled datasets tailored to the various ISAC settings. However, unlike in other fields where there is a long standing history of exploiting machine learning (ML), the ISAC research community has yet to establish a consensus on a set of commonly accepted datasets to evaluate and compare solutions for the diverse ISAC problems and scenarios. Existing datasets are often tied to specific research papers addressing the design and evaluation of a particular solution, covering a limited range of ISAC settings, and often providing data for a single site.

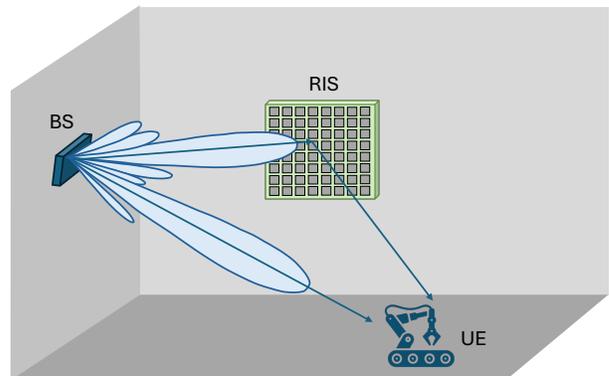
Regarding the methodology, two primary approaches have been used to generate current datasets: ray tracing and experimental measurements with real transceivers. The ray tracing methodology is attractive, especially when considering applications in outdoor scenarios, since it enables the collection of a large amount of data without the need of a costly experimental measurement campaign. Additionally, it allows for the simultaneous simulation of various sensors, such as radars, lidars, and cameras, within an electromagnetically simulated environment, as illustrated in Fig. 11. This capability provides a straightforward approach to creating multimodal datasets. There exist, however, several limitations associated with the ray tracing methodology. First, the accuracy of the data is significantly impacted by the level of detail in the simulated environment. For instance, simulating an outdoor environment without key elements like lampposts, traffic lights, windows, or metallic structures can result in channel measurements that capture fewer relevant paths. While this may not drastically impact the performance of a design for communication, it can substantially distort the results of ISAC solutions. Second, it is critical to use well-tested ray tracing software that accurately models various propagation mechanisms. For instance, an inaccurate implementation of diffuse scattering at mmWave frequencies can lead to errors in the locations of reflection points, significantly affecting the accuracy of the measured delays and distorting localization results. Third, it is important to recognize that ray tracing can only model the propagation channel in a practical manner. Other effects related to hardware impairments, which can affect sensing accuracy and may be addressed through data exploitation, still need to be incorporated using a model-based approach when creating the measurements of the received signal. While models for non-idealities such as beam squint, array calibration errors, and self-interference are generally well understood, further research is needed to identify which impairments should be included in the transceiver simulation, as they can significantly impact sensing performance—even if they were previously overlooked in communication-only system designs. Finally, another interesting working line involves the exploitation of generative AI for augmentation of datasets for ISAC.

### B. Machine Learning for ISAC

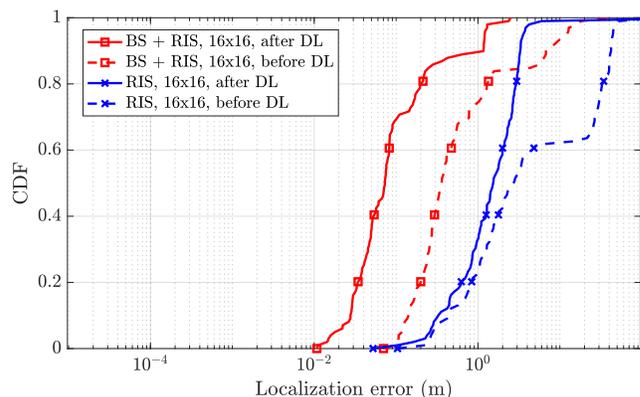
A fundamental question is when a data-driven approach should be adopted in the design of an ISAC system. Many data-driven solutions for an ISAC setting propose a black-box approach, where received samples are input into a deep network that extracts sensing or localization information. However, we argue that a wisely combined exploitation of models and data should be preferred. On the one hand, by combining model-based and data-driven stages in the overall design can be an effective solution for various ISAC challenges. On the other hand, well-understood models can inspire the development of deep networks tailored to specific ISAC applications, following a model-driven deep learning approach.

1) *ML solutions to handle model limitations*: Data-driven approaches can play a key role in managing the impact of limitations in the models being exploited. These limitations

include insufficient knowledge of the models for all the hardware impairments in the ISAC transceiver, uncertainties in the parameters of the models being exploited, or even the complete lack of a mathematical model. However, there is limited work on all these aspects.



(a)



(b)

Fig. 12. (a) System model of a RIS-aided localization system where the BS-UE link may or may not be blocked, and the RIS and arrays at the BS and UE have impairments. (b) Localization performance gain when antenna array impairments are mitigated by the use of a dictionary learning method which finds the non-ideal array manifold. The blue curves show the localization performance when the BS-UE link is blocked, and the signal only reaches the UE via RIS. Analogously, the red curves show the localization results when both the BS-UE and BS-RIS-UE links are available.

Array calibration, mutual coupling between antenna elements and inter-element distance perturbation are hardware impairments that can have a relevant impact on sensing performance [12]. Fig. 12 shows an example of the performance loss of a RIS-aided joint localization and communication system when these array impairments are introduced into the simulation. In this case, dictionary learning (DL) techniques can help to mitigate these effects by learning the array manifold that incorporates the impairments [16]. Autoencoders have also been proposed to deal with array impairments when solving the positioning problem, but only on a simplified single-target narrowband setting [17]. Further work is needed to derive deep networks for more complicated scenarios and other network sensing configurations, including the exploration of alternative deep networks. Data-driven methods could also play a key role to address other impairments such as lack of phase synchronization in distributed ISAC systems.

Regarding the uncertainties in the error models and trustability of the estimated parameters exploited for sensing, the impact in performance is especially relevant when the several multipath components exploited for sensing are estimated with different uncertainty levels. Model-based approaches have very limited ability to manage these different uncertainties, since their corresponding statistical priors are usually unknown. This is a clear example where deep learning can help. Along these lines, Transformers have been recently proposed to learn the inter-path relationships in multipath channel parameters and their trustability for position estimation. In addition, Transformers also show an impressive performance to predict movement patterns in position tracking problems [18]. These initial designs need to be extended to other more complicated ISAC settings, where multiple targets need to be localized or tracked.

2) *ML solutions to handle method limitations*: The design of ISAC transceivers is generally complex because both communication and sensing metrics have to be considered when optimizing the system. In addition, when exploiting MIMO architectures with large arrays, the dimension of the variables to be optimized are high. Furthermore, in many cases there are constraints associated with the specific circuit architectures being considered. As a result, the optimization problems that arise when dealing with various aspects of the ISAC system—for example precoder/combiner design or pilot design—are in general non convex, high-dimensional, and hard to solve. Only suboptimal solutions are often possible, usually requiring a high computational complexity. Finally, some stages of the ISAC system like the precoder and combiner have to be reconfigured for every frame, which introduces a constant high computational burden in the system, making it unfeasible in a practical scenario.

State-of-the-art data-driven approaches could provide either lower complexity solutions to the aforementioned problems or simply a feasible solution when the problem is too complex to be solved by conventional optimization techniques. Initial data-driven solutions only address, however, a limited number of ISAC settings and problems, mainly focusing on the waveform or the precoder/combiner design in joint radar and communication scenarios with a single BS [19]. The ML solutions that could handle method limitations can be extended in future work to joint beamforming design for distributed ISAC systems and spatial designs in the near field or mixed near field / far field scenarios, where the complexity of the signal models further complicates the problem.

The complexity issues in ISAC systems also appear in target/channel parameter estimation problems. Although there is on-going research on model-based approaches to solve these issues, model-driven deep learning also exploiting channel sparsity is an interesting alternative still to be further explored [20].

## VI. STRATEGY 5 – INTEGRATING OPERATION WITH ADVANCED HARDWARE

To enhance the performance and flexibility of ISAC systems, recent advances in hardware and electromagnetic theory

have introduced several innovative approaches. This section explores four key technologies: RIS, reconfigurable holographic surfaces (RHS), fluid antenna systems (FAS), and electromagnetic signal processing. This section outlines the operational advantages and current limitations of each technology, setting the stage for further innovation in ISAC hardware and processing frameworks.

### A. RIS-aided Localization and Sensing

RIS is a type of ultra-thin surfaces with programmable elements that can dynamically adjust their reflection properties, enabling precise control over signal paths. The primary advantage of the RIS for ISAC is its potential to provide high spatial resolution and improved signal control in multipath environments. In positioning applications, an RIS improves the spatial diversity by supporting high-precision angle measurements, making it particularly valuable in complex indoor or urban environments. For sensing applications, an RIS can allocate portions of the surface to different tasks by customizing the phase shifts, which enables it to simultaneously track targets and maintain data transmission with minimal infrastructure. Moreover, the ability of the RIS to operate as an additional reflection point can facilitate high-resolution detection and tracking, helping overcome challenges in scenarios where direct Line-of-Sight (LoS) communication is limited or obstructed.

Despite these potential benefits, RIS-aided ISAC systems face several notable challenges to be addressed. A primary difficulty arises from the frequency-dependent phase shift profiles, which lead to beam-splitting effects for wideband signals. While this beam-splitting can enhance sensing by creating spatially diverse paths, it often reduces communication rates due to misaligned beams across different frequencies. Additionally, there is a fundamental mismatch between the requirements for sensing and communication tasks. For optimal communication, the RIS aims to align the phases of all signal paths to maximize data rate; however, for sensing, randomizing the phase shifts can improve echo signal diversity and help distinguish between different targets. Another significant issue lies in the non-idealities of RIS hardware, which current ISAC models often overlook [21]. Practical RIS implementations suffer from effects like mutual coupling between elements [16] or “pixel” failures” [22], which can distort the reflected signals and reduce localization / sensing accuracy. Moreover, the RIS design and control complexity increases with environmental dynamics, as achieving optimal phase adjustments in a mobile setting with varying obstacles remains a substantial challenge.

### B. ISAC with Reconfigurable Holographic Surfaces

Traditional ISAC systems rely on power-consuming phased arrays to provide high spatial diversity, leading to a limited aperture size subject to a power budget. RHS, an innovative type of planar antenna with densely deployed metamaterial elements, is a cost-efficient alternative to the phased array, as it can dynamically tune the wave properties through simple diodes [23]. As a result, a larger aperture can be achieved to provide a higher directive gain with the same power

budget as the phased array. To be specific, the signal is first injected through feeds and then radiated to the free space through metamaterial elements. With tunable electromagnetic responses of the metamaterial elements, the RHS can produce a desired radiation pattern.

Although the RIS is also a metasurface, the RIS and the RHS are different in two aspects: First, the RIS reflects the signals to generate directional beams while the signals propagate along the RHS. This implies that the feed of the RIS is external while the feed of the RHS is internal, which makes the RHS easier to integrate with the transceiver as a light-weight and ultra-thin antenna and the RIS is more suitable for a passive relay; Second, all the elements of an RIS will reflect the signals simultaneously, but the RHS adopts a series feeding mechanism where the incident reference wave propagates along the waveguide, exciting each element one by one. This indicates that the elements of the RIS can be controlled independently while the configurations of RHS elements are coupled together through a unique constraint. To be specific, the operating mechanism of the RHS makes a gradual attenuation of the reference wave during its propagation process, as shown in Fig. 13, which brings a unique constraint, i.e., the sum of the radiated power from RHS elements should not be larger than the transmit power from the feed.

To achieve the ISAC functionality, an RHS is used for analog beamforming:

- *Sensing*: The sensing performance, which is shown as the radar utility in Fig. 13, is measured by the beam-pattern gains towards the desired directions and the cross-correlation among these directions. A high beam-pattern gain contributes to a higher signal-to-interference-noise ratio (SINR) of the echo signals while a low cross-correlation to separate the echo signals from different targets.
- *Communication*: The SINR of each user can be used to measure the communication performance.

The ISAC optimization problem can be formulated as the design of the analog and digital beamformers to maximize the radar utility given SINR and leakage power constraints [23]. A prototype and corresponding experimental measurement setting was reported in [24]. The experimental results in Fig. 13(b) revealed that the cost-effectiveness (defined as one minus the cost ratio of the RHS to the phased array under the same communication and sensing performance) is always greater than 0, which means that the cost of the RHS is lower than that of phased arrays.

However, there are still some open problems about how to incorporate the RHS into ISAC systems. First, the unique leakage power constraint makes existing waveform designs no longer applicable. Second, the design of the decision function to recognize objects needs further studies as it is coupled with the beamforming scheme.

### C. ISAC with Fluid Antenna Systems

The FAS represent a transformative technology in wireless communications by allowing antennas to dynamically change

their physical locations or configurations, which can significantly enhance sensing, positioning, and ISAC capabilities. Fluid antennas exploit spatial diversity by switching between multiple ports in response to channel conditions, offering a novel way to manage the fundamental trade-offs between communication and sensing functions in emerging multiuser MIMO and ISAC systems [25].

One of the primary opportunities of FAS lies in improving spatial degrees of freedom (DoF) for both sensing and communication. On the one hand, by enabling adaptive port switching, fluid antennas enhance the ability to sense and locate targets with high accuracy. For example, ISAC systems with fluid antennas can achieve superior spatial resolution due to the adjustable antenna positions, which yield better angle of arrival (AoA) estimation and reduce the ambiguity of fixed antenna systems. The flexibility offered by the FAS also helps to mitigate multipath interference, enhancing sensing performance in dense environments. On the other hand, fluid antennas allow multiuser MIMO systems to dynamically select port positions that minimize inter-user interference, increase system robustness, and improve the sum rate for users without compromising sensing accuracy. This adaptability is particularly valuable for ISAC, where maintaining both high-quality communication and reliable sensing signals is challenging in shared frequency bands.

Despite its potential, integrating the FAS into ISAC systems presents several technical challenges. One key issue is the need for accurate and fast and low complexity port selection algorithms that can adapt to changing channel conditions. Additionally, designing effective joint port selection and beamforming algorithms remains challenging due to the complexity of balancing the sensing and communication requirements. Another major issue involves hardware limitations, since the implementation of fluid antennas is still in the research stage. Finally, FAS systems face scalability problems, as managing multiple ports over large antenna arrays can significantly increase the cost and complexity of signal processing.

### D. Electromagnetic Signal Processing

The integration of electromagnetic signal processing (ESP) and electromagnetic information theory (EIT) presents new possibilities for 6G wireless applications in ISAC. EIT combines electromagnetic theory, antenna theory, wireless propagation modeling, and classical information theory into a cohesive framework, enhancing the handling of channel state information (CSI) across varied environments. This unification enables precise sensing and positioning. Moreover, EIT allows seamless integration of large-scale antenna arrays and stacked intelligent metasurfaces (SIMs) to enable continuous, high-accuracy localization and situational awareness in ISAC systems by jointly modeling antennas and wireless propagation for reliable data interpretation and high spectral efficiency.

One of the primary opportunities ESP and EIT offer is enhanced spatial resolution through wave-domain processing and fine-grained channel modeling. SIM technology, for instance, can process signals in the wave domain across multiple programmable metasurfaces, which enhances beamforming

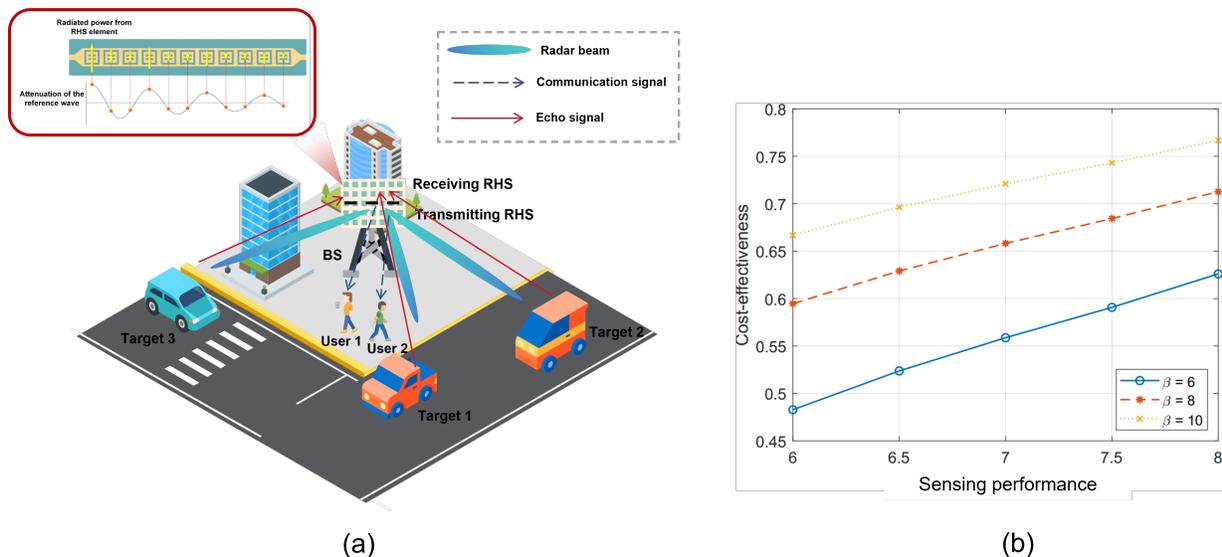


Fig. 13. (a) Illustration of an RHS and an RHS-aided ISAC system. The ISAC system is monostatic and the RHS is divided into two parts: one for transmitting and the other for receiving. (b) Cost-effectiveness comparison between the RHS and the phased array. The cost effectiveness is defined as the cost saving of using an RHS instead of a phased array with the same radar utility with  $\beta$  being the ratio of the antenna cost of a phased array to the cost of an RHS element.

and minimizes delay for real-time positioning applications. Additionally, the use over-the-air computation (AirComp) in ISAC networks, merges sensing, communication, and computation into a unified transmission [26]. This integration is valuable for positioning applications where AirComp leverages the superposition of analog-wave signals for accurate spatial estimates without the delay of traditional back-end processing.

Several challenges need to be addressed to fully realize ESP and EIT in sensing and ISAC. A key issue is the inherent trade-off in ISAC between the differing requirements for sensing and communication; sensing favors randomized phase shifts for signal differentiation, while communication demands aligned phase shifts for maximizing data rates. Additionally, the mutual coupling between SIM or large-scale antenna elements complicates channel modeling. Another significant challenge is the management of non-idealities in SIM and AirComp systems, such as synchronization across IoT devices for accurate signal fusion.

## VII. STRATEGY 6 – INTEGRATING SENSING, COMMUNICATION AND NETWORK OPERATION

In the previous sections we developed the vision for advanced forms of sensing that exploit the communication waveform. Now we address the dual paradigm, where the sensing information is exploited for enhancing the communication performance. Both conventional sensors and network sensing can be exploited, simultaneously or not, to enhance network operation. Exploiting sensor information is especially relevant at high frequencies, where effects like blockage and the large beam training and channel estimation overheads associated to the exploitation of large arrays become an issue.

Sensing can assist network operation in many different ways to mitigate the aforementioned challenges [1]. Prior work has extensively addressed the problem of sensor-aided beam

training, where different types of sensing information such as position, radar spatial covariance, images from cameras or lidars, range-Doppler data from monostatic network sensing—and even the multimodal fusion of several of these sources—are exploited to reduce the overhead associated to conventional beam training. Although not as studied as sensor-aided beam training, sensor-aided blockage detection has also been a topic of recent research. In the next subsections we discuss the interest of other advanced applications for sensor-aided communication that go beyond beam training and blockage detection.

### A. Environment-aware Channel Prediction

The overhead of CSI acquisition becomes a bottleneck in the performance of ISAC systems, especially when large antenna arrays and bandwidths are exploited to achieve high data rates and sensing accuracies while serving a high number of users. CSI prediction can alleviate this burden by providing a prior for CSI from out-of-band information. However, prior work on CSI prediction focuses on CSI translation from one band to another; in particular, downlink to uplink translation in frequency division duplexing systems, or statistical CSI translation in sub-6 GHz-aided millimeter wave systems.

Network sensing by itself or combined with standalone sensors by exploiting multimodal fusion can provide a new avenue for channel prediction exploiting a 3D reconstruction of the propagation environment, as illustrated in Fig. 14. Even if the electromagnetic properties of the reconstructed environment are not perfectly known, this kind of reconstruction can be exploited by electromagnetic simulation methods to obtain a prediction of the channel path parameters at a given user location. Furthermore, past channel estimates corresponding to previous user locations in that site could be stored in a database and jointly exploited with the environmental reconstruction by

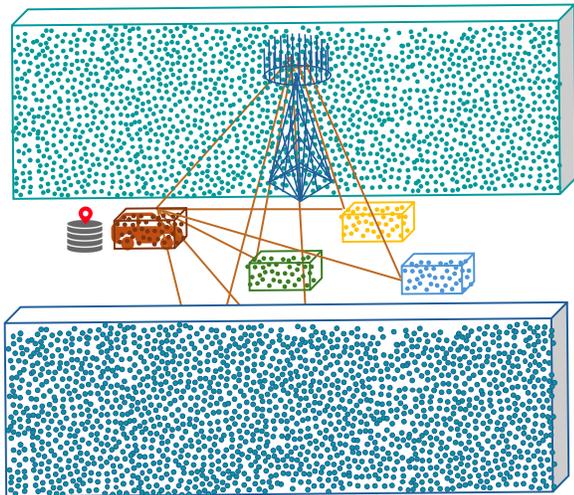


Fig. 14. A reconstruction of the 3D scene corresponding to a vehicular scenario created by network sensing, or multimodal fusion of standalone sensors and network sensing, is represented by the cloud points. The 3D scene reconstruction provides information about the propagation environment, in particular about the scattering polygons, that can assist channel prediction. This information together with a database of past channels associated to specific user locations can be exploited by deep learning strategies to predict the channel for a specific user. The rays corresponding to the predicted channel are represented with orange lines.

leveraging machine learning techniques to generate a better prediction for the CSI. Depending on the accuracy of the prediction, it could be directly exploited at the new user location or used as a prior for a more precise estimation based on very few pilots. Many challenges still need to be solved to make this approach a reality, including the high complexity of approaches for channel prediction based on electromagnetic simulation such as [27], mitigation of the impact of location errors in the predictions, or managing the large sizes of the database including past channel realizations.

### B. Link Self-configuration

The complexity of link configuration is growing as MIMO arrays get larger, bandwidths increase, and circuits / antennas become more reconfigurable to achieve high data rates and good sensing / localization. A main problem to be solved is to how to select from among the multitude of potential array configurations at both ends without consuming too many over-the-air resources. This is important because less overhead means more resources for communication and sensing objectives, with less energy wasted. We envision an approach where the network achieves self-awareness by leveraging sensing information to learn deep models that enable transceiver configuration with reduced overhead in dynamic propagation environments. The BSs will self-adapt in a site-specific manner to their local environment, while devices self-adapt based on their own unique configurations and usage. The learning will exploit patterns in different temporal and spatial scales, and will account for the growing heterogeneity of BSs and device types. The learning may be decoupled, with the BS and devices learning their own models, though will possibly

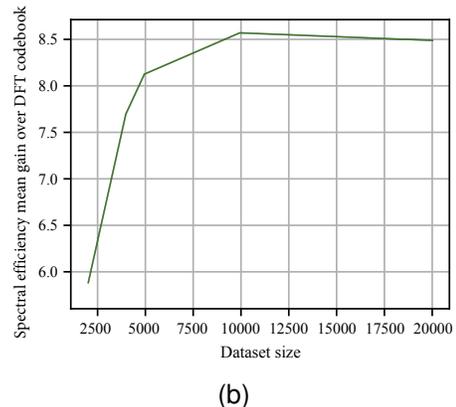
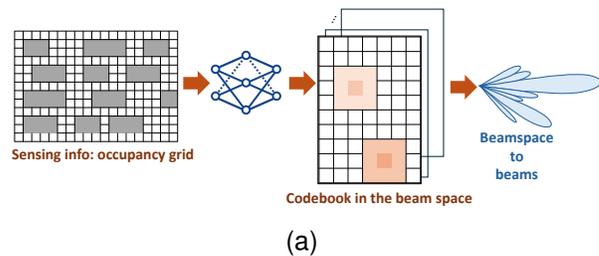


Fig. 15. (a) Block diagram of the codebook design strategy in [28] exploiting deep learning and sensing information. (b) Performance gain results (in natural units) at 28 GHz when compared to a DFT codebook.

exploit distributed or federated operation with sharing of data and models among peers.

Sensing information can play a key role in many configuration problems, thanks to congruences between sensed environment and radio propagation channel derived from a common underlying physical environment. Places where sensing information may play a role include the design of site/user specific optimizations, MIMO codebooks for beam training, pilot allocation for channel estimation, codebooks for channel state information feedback, power allocation, and rate adaptation.

In the particular problem of MIMO codebooks design, localization information is relevant. In a centralized approach to localization-aided beam training studied in prior work, the BS learns to recommend BS-user beam pairs from the BS and the user beam codebooks, based on localization information from current and past users in the cell. Using fixed beam codebooks and searching them in a centralized fashion are not well suited, however, for a resilient ISAC network. The BS may need to impose additional constraints and requirements on its beamforming to accommodate sensing, multiuser communication, or full duplex self-interference cancellation if performing monostatic sensing (causing it to either expand its beam codebook or deviate from it). Moreover, each BS and user may have different antenna array sizes and placements, not to mention hardware variations. As a conclusion, the BS and devices should each learn their own codebooks, and should learn their own recommendations from those codebooks.

Leveraging all the wealth of sensing data for MIMO beam codebook design is challenging. A potential approach is to use the sensing information to create occupancy grids that can be

combined with beamspace representations of the codebooks to exploit deep learning models for codebook adaptation [28], as illustrated in Fig. 15(a). The significant performance gain that can be achieved in a multiuser MIMO setting operating at 28 GHz can be observed in Fig. 15(b), that summarizes the results from [28], with a baseline system operating with a fixed DFT codebook. Though network self-adaptation exploiting sensing information is still in its infancy, examples like that in Fig. 15, show that there are important benefits in exploiting sensor information at a basic level. Much work remains in general at a fundamental level like how best to make use of sensor information, how to design lightweight models that can run on devices, how to learn across the network, and when to relearn.

### C. Proactive Blockage Management

Standalone sensors such as lidars and cameras have been proposed in recent work for reconstructing 3D scenes and predicting the trajectories of users and objects that can potentially create blockage. These predicted patterns can be used to make proactive frequency handover or BS selection decisions that avoid blockage occurrences and reduce the link outage probability. One obvious limitation of vision-aided proactive beam management is the availability of these sensors in the whole coverage area of the network. Moreover, optical sensors are vulnerable to obstructions and can only reliably operate in LOS conditions.

Different configurations of RF network sensing as well as different sensing modalities can help to overcome these limitations and mitigate the effects of failures in the optical imaging systems. Fusion of RF network sensing and optical sensing modalities, as discussed in IV, can significantly increase the accuracy and reliability of the predicted blockage patterns. Furthermore, multi-band network sensing, as proposed in Section III, can improve the resolution and accuracy of the images of the scene and also achieve a better trade-off between sensing coverage and resolution. These ideas open new opportunities to further enhance the beam management process and achieve a significant reduction of the link outage probability in next generation networks exploiting high frequency bands.

### D. Cross-Layer Perspectives on Sensing-Driven Network Operation

Sensing can influence not only the configuration of the physical layer but also network operation at various layers, including computation, storage, and backhaul [29]. Machine learning is expected to play a key role on providing solutions that integrate in a dynamic way the measurement capabilities of the physical layer with the network resources managed by upper layers, as illustrated in Fig. 16. This network-wise management of the resources available at different layers is especially interesting for ISAC networks, given the conflicting requirements to provide excellent performance for sensing, communication and computation and storage services. Solving challenges like synchronization or complex multi-resource allocation problems, and provide the backhaul requirements

that arise from tight integration between sensing and communication are still technological barriers to be overcome to enable this vision.

## VIII. CONCLUSIONS

In this paper, we presented six innovative integration strategies for enhancing the dual functionality of integrated sensing and communication (ISAC) systems in 6G and beyond. Next, we summarize the key messages for each integration strategy discussed in the previous sections:

- *Integration of Multiple Network Elements:* We highlighted the benefits of coordinating multiple ISAC nodes, such as base stations (BSs), user equipment (UEs), and non-terrestrial infrastructure (e.g., UAVs and satellites), to improve sensing coverage, accuracy, and reliability. The coordination allows coherent and incoherent fusion of measurements, where coherent fusion enhances spatial resolution but imposes stricter synchronization requirements. Multistatic configurations, involving monostatic and bistatic sensing, introduce additional spatial diversity that improves resolution and reduces ambiguities. However, challenges such as synchronization across nodes and maintaining phase coherence must be addressed to fully exploit these benefits.
- *Integration of Multiple Frequency Bands:* Multi-band ISAC offers the flexibility to adapt to varying propagation conditions, resolution needs, and target types by leveraging diverse frequency bands (e.g., FR1, FR2, FR3, and sub-THz). Different bands provide complementary sensing capabilities—low-frequency bands support penetration and coverage, while higher frequencies deliver finer resolution. We discussed coherent and non-coherent approaches to fusing multi-band measurements, emphasizing that coherent fusion demands tight synchronization. Additionally, challenges such as accurate channel parameter estimation across bands and balancing trade-offs between resolution and ambiguity were identified as critical research areas.
- *Integration of Sensing Configurations and Modalities:* Combining monostatic, bistatic, and multistatic sensing configurations enables richer environmental awareness. Monostatic sensing offers simplicity and tight clock alignment, while bistatic and multistatic sensing introduce additional spatial perspectives, enhancing resolution and robustness. Fusion of terrestrial and non-terrestrial sensing further extends sensing capabilities to global scales. Moreover, integrating external sensors (e.g., radar, lidar, and GPS) with ISAC data enhances situational awareness, but requires advanced fusion techniques to overcome challenges like synchronization, data association, and format differences.
- *Balancing Model- and Data-Driven Solutions:* We emphasized the importance of combining well-established mathematical models with data-driven approaches to address ISAC challenges. While models are effective in capturing system dynamics, they may fail under hardware impairments, uncertainties, or complex settings.

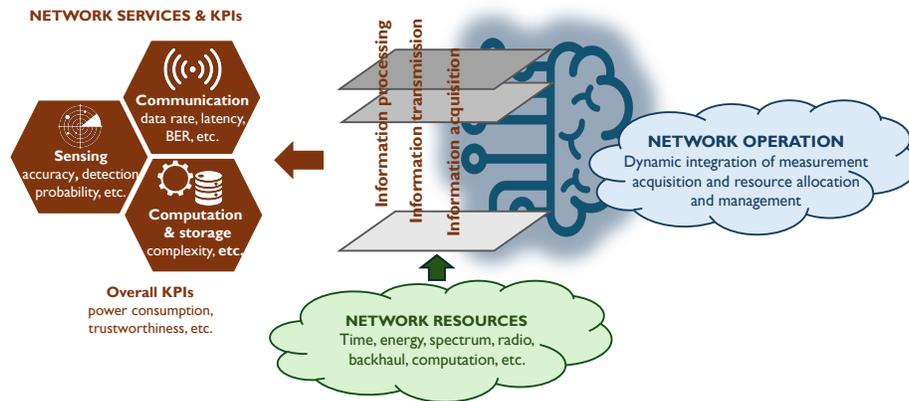


Fig. 16. ML-driven network operation that seamlessly integrates tasks related to resource allocation and management for information acquisition, transmission, and processing, enabling the dynamic optimization of trade-offs between KPIs for communication, sensing, and computation services.

Data-driven techniques, such as machine learning, offer solutions to these limitations. Examples include dictionary learning for hardware impairments, deep learning for CSI prediction, and AI-based fusion for managing multi-path parameter uncertainties. Developing reliable datasets, handling method complexity, and ensuring scalable learning frameworks remain open challenges in this strategy.

- *Operation with Advanced Hardware:* Advanced hardware technologies such as reconfigurable intelligent surfaces (RIS), reconfigurable holographic surfaces (RHS), and fluid antenna systems (FAS) open new possibilities for ISAC. RIS can dynamically optimize reflection paths for both sensing and communication, while RHS provides cost-effective solutions for large apertures, improving spatial resolution. FAS, with its adaptive port switching, enhances spatial degrees of freedom, supporting flexible beamforming for ISAC. Additionally, electromagnetic signal processing (ESP) and stacked intelligent metasurfaces (SIMs) enable high-accuracy localization and efficient integration of communication and sensing. However, overcoming hardware imperfections and developing low-complexity control algorithms remain critical challenges.
- *Integration of Sensing, Communication, and Network Operation:* Sensing information can significantly enhance network operation by enabling environment-aware channel prediction, proactive blockage management, and link self-configuration. For instance, sensing-assisted CSI prediction reduces the overhead of CSI acquisition by leveraging 3D environmental reconstructions and historical data. Link self-configuration exploits sensing information to dynamically adapt transceiver settings, optimizing resource utilization. Additionally, proactive blockage management combines network sensing with external sensors to predict and mitigate blockages, ensuring link reliability. Cross-layer optimization further integrates sensing data with network-level decisions to balance communi-

cation, sensing, and computation resources effectively.

The avenues discussed in this paper provide a foundation for future research, and we encourage further exploration of these strategies to realize the full potential of ISAC in 6G and beyond.

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