

Perspective

Energy-Efficient Cell-Free Integrated Sensing and Backscatter Communication for Sustainable Networks

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Abstract

The rapid expansion of smart city infrastructures and Internet of Things (IoT) networks has led to extremely dense wireless deployments, driving unsustainable energy consumption and exacerbating environmental concerns. To improve sustainability in the long term, future wireless systems must fundamentally prioritize energy-efficient and autonomous operation. Integrated sensing and communication (ISAC) is emerging as a key enabler for next-generation systems by jointly supporting sensing and communication through shared spectrum, hardware, and signal processing resources. In IoT systems, sensing of target parameters, e.g., range, angle, velocity and identity, etc., form the basis of autonomous and environment-aware applications. However, this integration increases overall power consumption due to the added coordination overhead and the workload placed on shared hardware components. To this end, backscatter communication provides a low-power alternative that enables passive data transmission through energy harvesting and sharply reduces the need for active radio circuits. However, the coexistence of sensing and backscatter functions introduces mutual interference, which often requires large multiple-input multiple-output (MIMO) arrays for effective mitigation. Furthermore, sensing performance depends heavily on line-of-sight conditions, while backscatter links operate only over short ranges. Although increasing array size or transmit power can extend coverage, it imposes substantial energy and hardware costs and undermines sustainability goals. To address these limitations, cell-free MIMO is emerging as a promising candidate technology for next-generation systems. Cell-free MIMO relies on a dense deployment of distributed access points that cooperate to serve devices across a wide area. This cooperation enables effective beamforming and interference management, providing spatial diversity comparable to large, centralized antenna arrays without incurring their associated hardware or power costs. They also enable aggregation of weak double-hop reflections, reduced effective-illumination distances, multi-view sensing, and robustness to blockage, which is invaluable to backscatter communication. This perspective article introduces the foundations, challenges, and architectural considerations of cell-free backscatter-aided integrated sensing and communication (CF-BISAC) systems. By leveraging the advantages of battery-less backscatter IoT devices and the distributed nature of cell-free MIMO, CF-ISABC aims to maximize sensing and communication performance under strict energy constraints, contributing toward energy-aware ISAC systems capable of supporting high-density, low-power wireless applications.



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Keywords: backscatter communication; cell-free MIMO; integrated sensing and communication; energy efficiency; fluid antenna; reconfigurable intelligent surfaces; pinching antenna

1. Introduction

The extreme proliferation of Internet of Things (IoT) applications has created an unprecedented scale of networking which is expected to extend the number of machine-to-machine subscriptions to 97 billion [1]. This also diversifies the types of applications and necessitates that 6G systems support not only reliable data transmission but also continuous awareness of the physical environment. Furthermore, this massive inclusion of devices infeasibly scales the energy footprint [2,3]. Modern applications, e.g., autonomous transportation and industrial networks [4], etc., rely on real-time information about the objects. As a result, sensing has become a fundamental network capability for next-generation systems. Sensing functions include the estimation of target and environment parameters, e.g., range, angle, velocity, and identity, etc. This requirement is explicitly included in the IMT-2030 vision, which identifies environmental perception and localization as a core performance metric for 6G systems. Conventional sensing systems are deployed independent of communication networks, which leads to inefficient spectrum utilization, high energy footprints, sustainability challenges, additional infrastructure, and increased deployment cost. This is not scalable for dense and ubiquitous deployments of next-generation systems. This motivates the integration of sensing functions directly into the communication infrastructure.

To this end, integrated sensing and communication (ISAC) is emerging as a promising paradigm for energy-efficient 6G systems. ISAC enables joint sensing and communication functions in a single network architecture to improve spectrum efficiency, energy efficiency, and hardware costs by sharing network resources [3,5,6]. ISAC systems utilize target signal reflections to estimate information about objects of interest while simultaneously delivering data services. This joint operation enables spectrum reuse, reduces hardware redundancy, and allows sensing and communication to simultaneously be realized. As a result, ISAC provides a unified framework for data transmission and environmental perception. However, integrating sensing and communication introduces fundamental challenges. Sensing relies on reflected signals which experience multiplicative path loss over the forward and backward propagation paths. This reduces the signal power received at the sensing system. To mitigate this effect and enable reliable parameter estimation, high transmit power, wide bandwidth, and large antenna apertures can be utilized, which increase energy consumption. In addition, joint operation introduces strong interference between sensing and communication components, complicating interference management. Sensing performance further degrades in cluttered environments where line-of-sight (LoS) conditions are not available. Conventional multiple-input multiple-output (MIMO) arrays have been explored for ISAC systems in the latest literature [7–10]. These systems employ multiple antennas at the transmitter/receiver to exploit spatial diversity and multiplexing gains, which improves spectral efficiency, link reliability, and interference management. Depending on the deployment, these systems can be configured as single-input multiple-output (SIMO) [11], multiple-input single-output (MISO) [12], and multiple-input multiple-output (MIMO) architectures. These configurations depend on the number of transmit and receive antennas and directly influence the achievable spatial diversity, beamforming capability, and sensing resolution in ISAC systems.

However, centralized MIMO-based ISAC architectures rely on colocated antenna arrays to illuminate targets and process reflected signals, which limits sensing performance under practical propagation conditions. It also necessitates high transmit power and wideband signaling to ensure detectable reflections from double-hop propagation. The use of extremely large antenna arrays (ELAAs) may improve performance, but it introduces near-field effects which are sensitive to mobility and synchronization [13]. Furthermore, centralized arrays provide a single spatial observation point, making sensing performance

highly sensitive to blockage, non-LoS propagation, and environmental clutter. These limitations become more pronounced in dense deployments and high-mobility scenarios. Cell-free architectures partially mitigate these limitations by distributing APs over the coverage area and enabling cooperative reception.

Distributed APs reduce the effective transmitter (Tx) to receiver (Rx) distance, increase the likelihood of LoS links, and provide spatially diverse observation points for multi-perspective sensing. They act as cooperative illuminators/readers which enable energy-aware illumination, scheduling and sensing in dense IoT networks. While centralized ELAA ISAC demands high illumination power and tight calibration, cell-free ISAC shortens effective paths, aggregates weak reflections, and improves robustness with lower energy cost. Furthermore, cooperative processing allows weak reflections to be aggregated across multiple locations, improving detection reliability and sensing accuracy in obstructed environments.

Despite these advantages, cell-free ISAC systems still rely on active transmission to communication. Dense IoT applications predominantly require numerous low-rate transmissions at massive scale. The energy cost associated with such systems remains a limiting factor. In this context, backscatter technology provides a compelling solution by enabling communication through controlled reflection of existing RF signals. Backscatter devices operate without active RF chains and consume orders of magnitude less power than conventional transmitters [14]. Since sensing in ISAC already relies on reflected signals, backscatter-based communication integrates naturally into the ISAC framework [15]. By embedding information into the reflected signals, the same RF signal can simultaneously support sensing and data transmission without additional spectrum or waveform generation. Moreover, cell-free MIMO allows the aggregation of weak double-hop reflections, reduces the effective illumination distance, enables multi-view sensing, and provides increased robustness to blockage, which is beneficial for backscatter communication. By leveraging the distributed structure of cell-free architectures and the low-power operation of backscatter communication, cell-free backscatter-aided integrated sensing and communication (CF-BISAC) emerges as a promising evolution for next-generation ISAC systems, enabling improved energy efficiency and scalability.

While cell-free ISAC systems and backscatter-aided ISAC systems have been studied independently, the convergence of these technologies remains fragmented in the literature [16–25]. This article provides the first comprehensive exploration of CF-BISAC systems which unifies the foundational principles, motivations, architectures, configurations, challenges and future directions of CF-BISAC systems with energy efficiency considerations. Existing works predominantly focus on the independent exploration of backscatter technology and cell-free MIMO for ISAC systems. Simultaneously, research in cell-free MIMO and backscatter communication systems largely omits sensing functionality [26–35]. In light of these research gaps, this work aims to explore the convergence of cell-free MIMO and backscatter technology for ISAC systems. We provide a detailed overview of cell-free MIMO and backscatter-based ISAC systems. We also discuss the energy efficiency limitations of conventional ISAC architectures and motivate the integration of cell-free MIMO with backscatter technology in this context.

We also introduce and elaborate the different configurations and architectures of CF-BISAC systems, with a directed focus on their system models, advantages and challenges. This work also systematically categorizes the energy efficiency challenges unique to CF-BISAC systems, e.g., Doppler effects, channel reciprocity, channel calibration, synchronization, fronthaul and back-haul capacity, etc. We then introduce emerging research directions for sustainable CF-BISAC systems, including reconfigurable antenna technologies, meta-backscatter systems, smart environments, next-generation MIMO, and large

language models, etc. The aforementioned positions this article as a taxonomy and research roadmap—from an energy-centric perspective—for CF-BISAC systems. A summary of the article organization is provided in Figure 1, and a list of abbreviations is shown in Table 1.

Table 1. List of abbreviations used in the article.

Abbreviation	Definition
IoT	Internet of Things
6G	Sixth-Generation (wireless) Communication Systems
IMT-2030	International Mobile Telecommunications 2030 (6G vision framework)
ISAC	Integrated Sensing and Communication
MIMO	Multiple-Input Multiple-Output
ELAA / ELAAs	Extremely Large Antenna Array / Extremely Large Antenna Arrays
LoS	Line of Sight
AP / APs	Access Point / Access Points
CPU	Central Processing Unit
Tx	Transmitter (or transmit)
Rx	Receiver (or receive)
CSI	Channel State Information
CF	Cell-Free
CF-MIMO	Cell-Free Multiple-Input Multiple-Output
CF-ISAC	Cell-Free Integrated Sensing and Communication
RF	Radio Frequency
BackCom	Backscatter Communication
RF-ID	Radio-Frequency Identification
BISAC	Backscatter-Aided Integrated Sensing and Communication
SINR	Signal-to-Interference-plus-Noise Ratio
mmWave	Millimeter Wave
UAV	Unmanned Aerial Vehicle
RIS / RISs	Reconfigurable Intelligent Surface / Reconfigurable Intelligent Surfaces
NCR / NCRs	Network-Controlled Repeater / Network-Controlled Repeaters
LLM / LLMs	Large Language Model / Large Language Models
AI	Artificial Intelligence
CAP	Continuous Aperture (as in CAP MIMO)
CAP MIMO / CAP-MIMO	Continuous Aperture (CAP) Multiple-Input Multiple-Output
XL-MIMO	Extra-Large Multiple-Input Multiple-Output
NF	Near-Field
FF	Far-Field

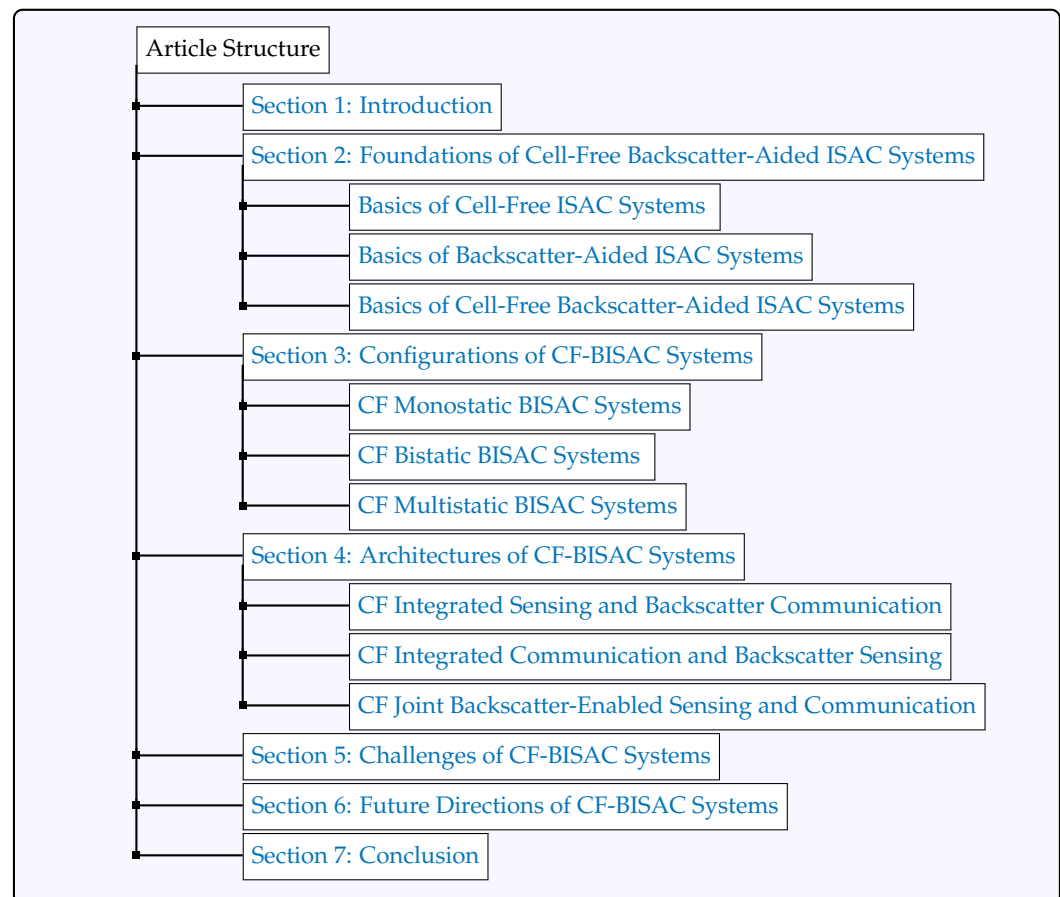


Figure 1. Overview of article organization.

2. Foundations of Cell-Free Backscatter-Aided ISAC Systems

In this section, we introduce the fundamental principles underpinning cell-free backscatter-aided integrated sensing and communication (CF-BISAC) systems.

2.1. Basics of Cell-Free ISAC Systems

Cell-free (CF) MIMO is a distributed network architecture in which many spatially distributed access points (APs) are connected through fronthaul links to a central processing unit (CPU), as shown in Figure 2. These APs jointly serve network devices over the same time-frequency resources using coordinated processing. Unlike conventional cellular systems, CF-MIMO does not realize fixed cell boundaries. Consequently, user associations are not limited to a single base-station. All APs participate in transmission and reception through coordinated processing which is based on the exchange of channel state information (CSI) which is acquired locally at each AP and aggregated at the CPU. This coordinated processing-based distributed architecture enables coherent or non-coherent combining of signals received from multiple spatial locations, which provides macro-diversity and uniform service quality across the coverage area. The distributed APs alter the signal models fundamentally and reduce the effective Tx–Rx distance, which mitigates the severe path-loss and blockage effects in cluttered environments. Cooperative reception across APs allows weak signals to be collected from multiple spatial localities. These signals are aggregated and jointly processed, hence improving system reliability in dense, cluttered, and non-LoS environments. These properties make CF-MIMO particularly suitable for large-scale IoT deployments, where devices are densely distributed and must realize real-time environment perception.

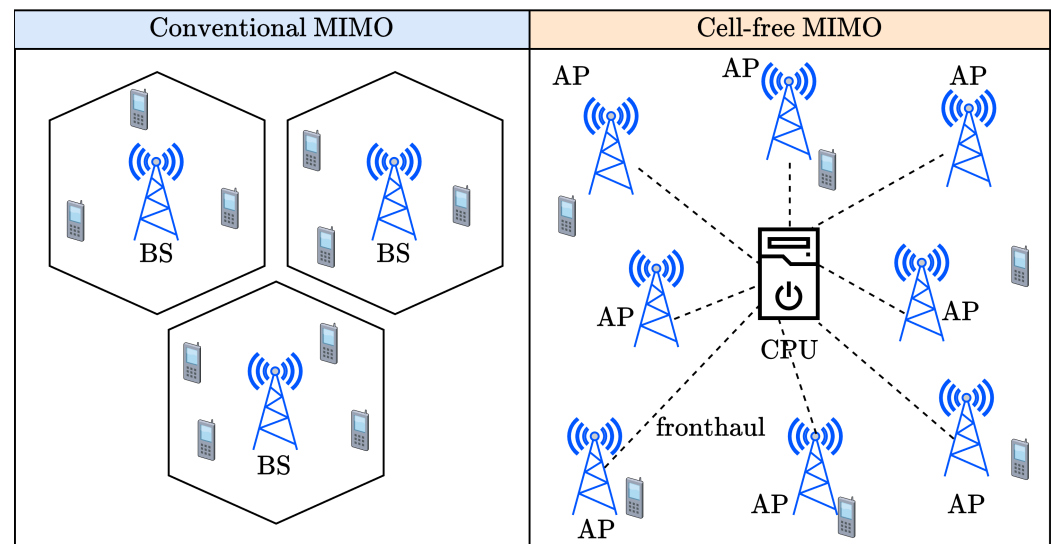


Figure 2. Comparison of the system architectures for conventional MIMO and cell-free MIMO systems.

These advantages of CF-MIMO have motivated its investigation for ISAC systems [21–25]. In ISAC systems, sensing functions rely on reflected RF signals to estimate parameters which are constrained by cluttered environments, limited spatial aperture and colocated antenna arrays. Reflected signals experience multiplicative path loss over the forward and backward propagation paths, which significantly attenuates sensing echoes. To mitigate this, centralized ISAC systems typically rely on high transmit power, wide bandwidth, or ELAAs, which increase energy consumption and hardware complexity. Spatially distributed APs provide multiple observation points for sensing, and enable multi-perspective sensing, which improves parameter estimation. The shorter propagation paths and increased likelihood of LoS links improves sensing reliability in obstructed and cluttered environments. Furthermore, cooperative processing allows weak sensing echoes to be detected without relying on excessive transmit power. Despite these advantages, CF-ISAC are characterized by massive numbers of low-rate devices, for which the cumulative energy cost of active transmission remains significant. While CF-ISAC improves sensing reliability and coverage, the advanced cooperative processing overhead, synchronization feasibility, illumination control, and fronthaul requirements become more challenging.

2.2. Basics of Backscatter-Aided ISAC Systems

Backscatter technology enables wireless data transfer by encoding information onto the incident radio-frequency (RF) signals through controlled reflection, as shown in Figure 3. These signals can be generated by a conventional transmitter, as is the case in ISAC systems, or an emitter/illuminator in dedicated backscatter systems. This encoding is achieved by switching the load impedance connected to the backscatter tag antenna [2,13,31,32,35–50]. The reflected signal is then observed by a receiver, conventionally called a reader, and subsequently decoded. Since the backscatter tags do not generate RF carriers, backscatter operation consumes orders of magnitude less power than traditional RF chains [51]. It enables microwatt power consumption in IoT systems [33]. Furthermore, since backscatter tags do not require power-hungry RF components, the total energy consumption scales weakly with the number of deployed devices, enabling dense large-scale IoT and sensing networks without a proportional increase in active transmission power. The energy flow of backscatter communication and sensing operation is shown in Figure 4. However, the

passive operation of backscatter devices fundamentally limits their achievable throughput, resulting in low data-rate communication.

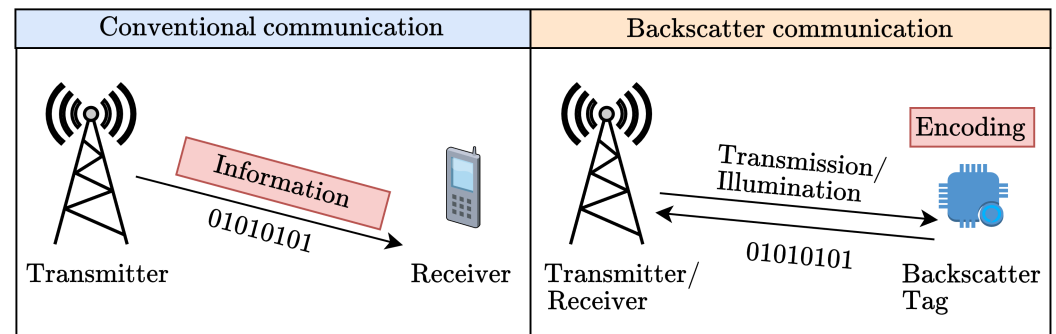


Figure 3. Comparison of system models for conventional communication and backscatter communication.

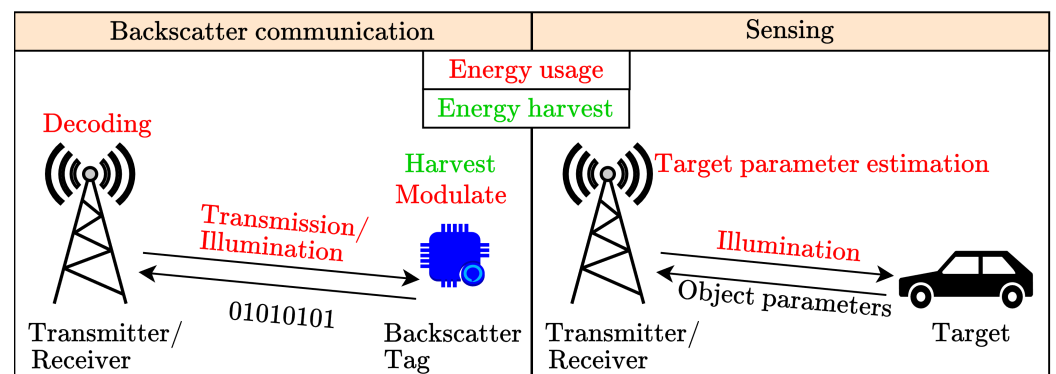


Figure 4. Illustration of the energy flow for BackCom and sensing operations in ISAC systems.

This property makes backscatter technology suitable for large-scale, low-data-rate deployments where battery replacement or wired power supply is impractical. Owing to these advantages, backscatter communication (BackCom) has been deployed extensively in radio-frequency identification (RF-ID) systems for inventory management, logistics, industrial automation, and asset tracking, etc. The latest works have extended backscatter operation to ambient RF environments, where existing cellular, Wi-Fi, or broadcast signals serve as signal illumination sources [52–56].

As sensing functions rely on the reception and processing of reflected RF signals to extract information about the environment, e.g., the presence, location, and motion of objects, BackCom can enable ISAC functions [16–20]. Backscatter devices operate on the same physical principle by encoding information onto reflected RF signals through controlled impedance modulation [57]. This reliance on signal reflections makes backscatter technology seamlessly compatible with sensing-focused wireless systems. This reuse of reflections improves spectral efficiency and reduces the reliance on high-power signal transmission, which are typically required to achieve accurate sensing in conventional systems. These considerations have motivated the investigation of BISAC systems [16–20,50,58–63].

Furthermore, backscatter devices can be used to design device-based sensing targets, which can provide target identification functionality in addition to conventional target detection. Strategic placement of backscatter tags can create additional reflective paths and virtual line-of-sight (LoS) links, which further improves sensing reliability.

2.3. Basics of Cell-Free Backscatter-Aided ISAC Systems

In this section, we discuss the foundations of CF-BISAC systems. CF-BISAC systems are characterized by cell-free transceivers, which serve conventional communication users, sensing targets, and backscatter devices, to enable sustainable and energy-efficient ISAC systems, as shown in Figure 5.

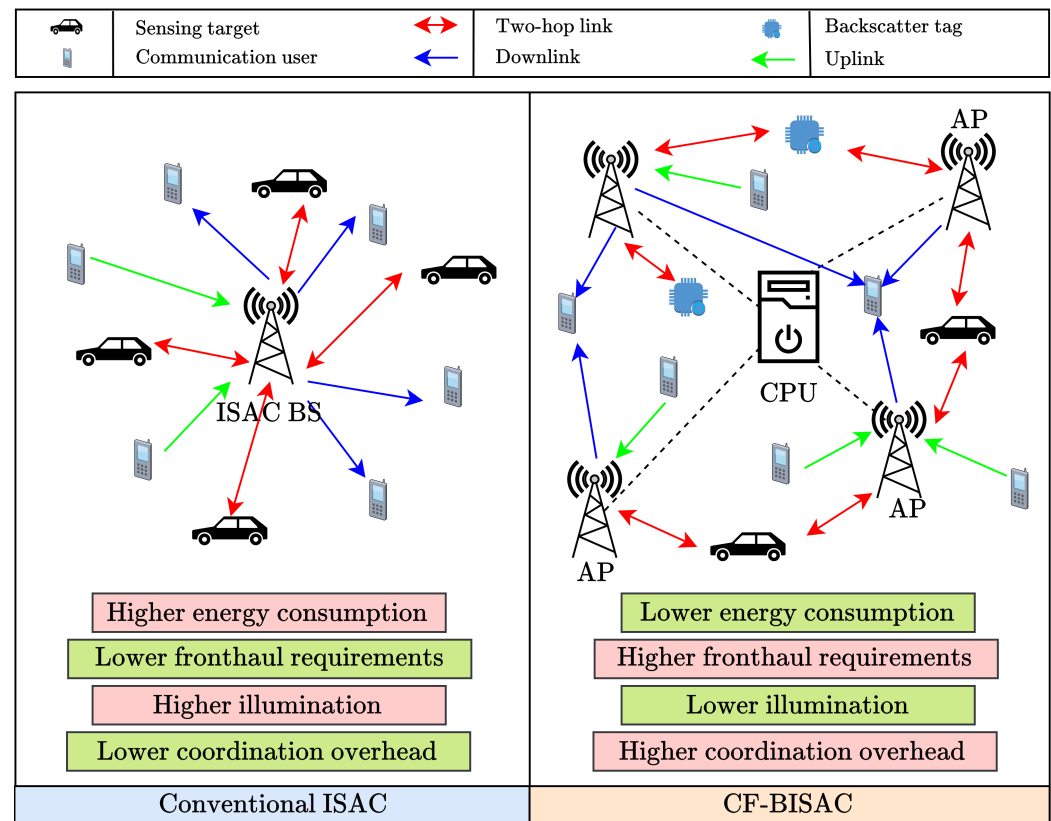


Figure 5. Comparison of system models for conventional ISAC systems and CF-BISAC systems.

2.3.1. Functions of CF-BISAC Systems

The inclusion of backscatter devices in CF-ISAC systems enables two different sensing functions: target detection and target identification. The functions are shown in Figure 6. In addition to low-power data transfer, these functions support dense and scalable IoT applications. Target detection enables the estimation of target parameters, e.g., range, angle, or motion, etc. from the reflected RF signals [23,64–66]. This is realized by utilizing distributed APs which collect backscattered and conventional echoes from multiple reference locations, which improves detection reliability in cluttered and blocked environments. The CF architecture also provides more LoS links to objects of interest, and generally decrease the Tx–Rx distance by using distributed APs. This enables the aggregation and processing of weak reflections which would otherwise be undetectable at a single, centralized BS, hence improving robustness in cluttered environments.

Target identification is enabled using device-based targets which utilize backscatter tags to encode device-specific information onto the reflected RF signal. In CF-BISAC systems, target identification is naturally enabled as the same reflected RF signal can carry both target-specific information and the data associated with a specific tag. The distributed APs enhance identification by allowing multiple APs to jointly observe tag-modulated reflections, which improves sensing resolution. As a result, CF-BISAC systems can simultaneously support detection of untagged targets and identification of tagged objects within the same spatial region.

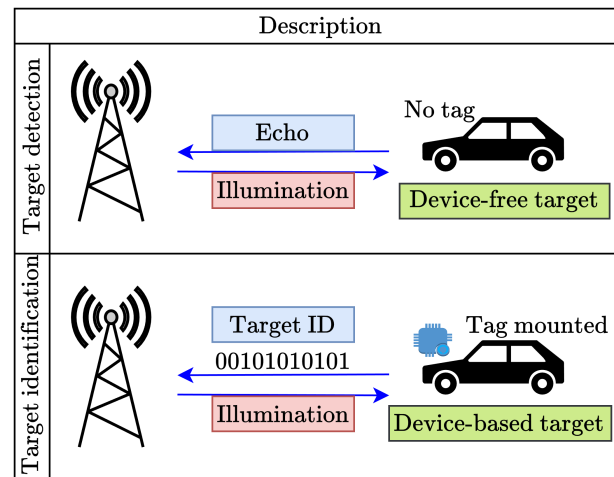


Figure 6. Different functions of CF-BISAC systems: target identification and target detection.

2.3.2. Types of Tags in CF-BISAC Systems

The energy efficiency, spectral efficiency, and functions of CF-BISAC architecture depend on the type of backscatter tags employed in the system design. These tags are summarized in Table 2. Passive backscatter tags operate entirely using incident RF energy and modulate the reflected signals without any onboard power source. These tags achieve the highest energy efficiency and enable long-term, maintenance-free deployment at large scale. This makes them ideal for dense IoT scenarios, e.g., inventory tracking [67], asset identification [68], and health monitoring [69], etc., where battery replacement is impractical. However, the lack of onboard power limits the achievable data rate and real-time sensing capabilities. In CF-BISAC systems, distributed APs mitigate these limitations by improving illumination and reception diversity. Semi-passive backscatter tags separate the powering of RF signal transmission and modulation [31,70,71]. Their onboard power source enables real-time sensing and data collection, which improves system reliability. This enables the support of integrated sensing functions, e.g., environmental measurements, which make them suitable for applications including smart infrastructure monitoring, industrial sensing, and wearable devices, which require real-time monitoring. The additional circuitry increases hardware complexity and power consumption compared to fully passive tags.

Table 2. Comparison of energy consumption of different backscatter tags in CF-BISAC systems.

Feature	Passive	Semi-Passive	Active	Ambient	Reconfigurable
Power Source	Harvested RF only	Battery for sensing and control	Battery-powered RF components	Ambient RF sources	Battery-assisted or hybrid
Energy Efficiency	Very high	High	Moderate	Very high	Moderate to high
Data Rate	Very low	Low to moderate	High	Very low	Flexible
Sensing	On illumination	Real-time	Advanced	Opportunistic	Adaptive

Active backscatter tags include active RF components to amplify or regenerate signals but still modulate reflection instead of transmitting like a conventional RF chain [40]. These tags enable higher data rates and extended communication range, but their reliance on active transmission reduces energy efficiency and increases hardware complexity. As a result, active backscatter tags are typically considered only in scenarios where perfor-

mance requirements outweigh energy constraints, such as specialized sensing or short-term deployments.

Ambient backscatter tags exploit uncontrolled RF sources, such as cellular or Wi-Fi signals, as illumination sources [72–74]. This eliminates the need for dedicated transmitters and emitters, improves spectral efficiency, and reduces infrastructure requirements. However, the lack of control over the illumination waveform affects the efficiency of tag modulation and sensing performance. In CF-BISAC systems, the presence of multiple distributed APs improves robustness by increasing the probability of illumination and reliable reception, making ambient backscatter suitable for opportunistic sensing and low-rate communication.

Programmable or reconfigurable backscatter tags enable dynamic control of reflection coefficients or modulation states, allowing adaptation to channel conditions and system requirements [43]. These tags support flexible operation, improved interference management, and enhanced sensing resolution at the cost of more complex control logic, more power usage, and hardware complexities.

2.3.3. Processing in CF-BISAC Systems

In CF-BISAC systems, each AP performs local signal processing using the available channel information and forwards the processed information to a central processing unit (CPU) through fronthaul links. The CPU applies joint processing to recover communication data and estimate sensing parameters by exploiting spatial diversity of distributed APs, which is essential for recovering weak backscatter. Joint processing also improves detection sensitivity and identification accuracy by using multi-perspective sensing.

In contrast, conventional ISAC systems rely on colocated arrays to perform sensing and communication, which limits spatial observation diversity and increases the sensitivity to cluttered and blocked environments. This motivates the deployment of extremely large antenna arrays (ELAAs), which experience fundamental changes in wave propagation by operating in the near-field region [75–85]. Near-field propagation introduces spherical wavefronts and strong spatial non-stationarity, making system performance more sensitive to mobility and calibration errors. These effects increase processing and beam training complexity in centralized ISAC systems which rely on a single large aperture. This consequently decreases energy efficiency and sustainability. CF-BISAC reduces reliance on ELAAs by exploiting distributed reception across multiple APs. This provides spatial diversity without requiring a single large array. However, CF-BISAC processing introduces additional requirements on fronthaul capacity, infrastructure, synchronization, and coordination among APs. These requirements increase system complexity and impose practical constraints on real-time joint processing in mission-critical ISAC systems.

3. Configurations of CF-BISAC Systems

The configurations of CF-BISAC systems are shown in Figure 7, and summarized in Table 3.

Table 3. Comparison of different configurations of CF-BISAC systems.

Configuration	CF-M-BISAC	CF-B-BISAC	CF-Mlt-BISAC
System model	Multiple APs acquire signal reflections which are combined through cooperative processing.	Transmission/illumination and reception are separated across APs.	Multiple APs act as illuminators and receivers simultaneously, forming multiple signal paths which are jointly processed across the network.

Table 3. Cont.

Configuration	CF-M-BISAC	CF-B-BISAC	CF-Mlt-BISAC
Sensing performance	Limited geometric and perspective diversity due to single-view monostatic observation geometry.	Higher range and angular resolution owing to spatial separation between Tx and Rx.	Highest resolution enabled by multi-perspective sensing from multiple APs.
Interference	Colocated Tx and Rx create strong self-interference.	Reduced self-interference owing to physical separation of Tx and Rx APs.	Self-interference varies across APs.
Channel estimation model	Cascaded channel is locally observed at each AP.	Cascaded channel spans multiple APs so estimation requires coordination.	Cascaded channel spans multiple APs so estimation requires coordination.
Sync. requirements	Local Tx–Rx synchronization at each AP.	Synchronization between Tx and Rx APs is required.	Most stringent synchronization across many APs.
Fronthaul and coordination load	Moderate as local processing can enable parameter estimation.	Higher owing to coordination of information between Tx/Rx.	Highest owing to coordination between multiple APs.
Reliability	Sensitive to blockage in monostatic configuration.	More robust owing to Tx/Rx separation.	Most robust, as alternate Tx/Rx pairs can be utilized.
Energy efficiency	High, but have continuous self-interference cancellation which consumes energy.	Higher owing to reduced self-interference and distributed sensing.	Variable, owing to multi-static sensing.

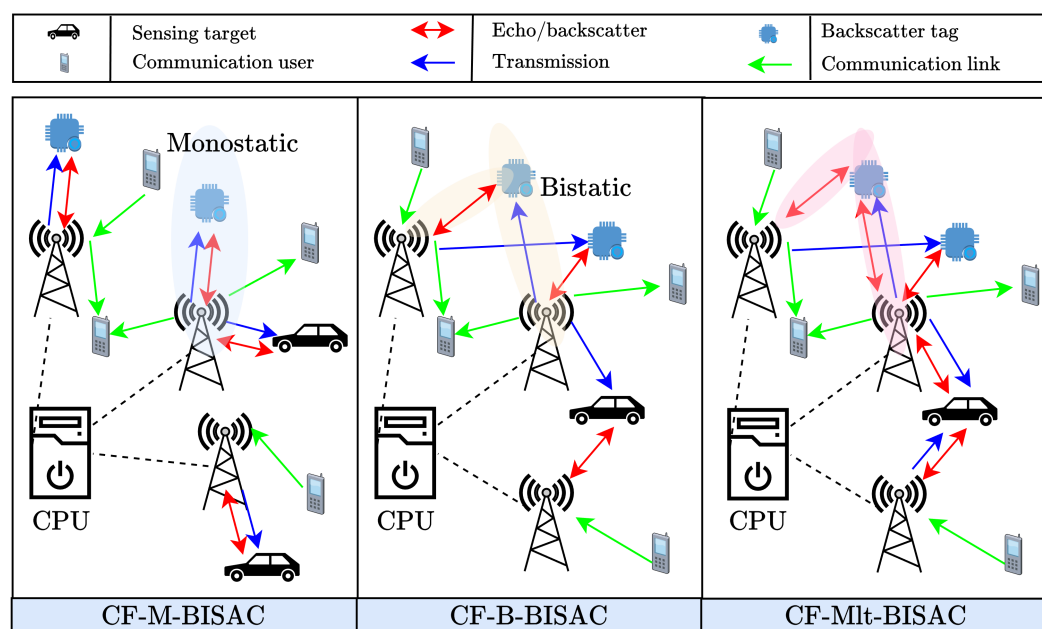


Figure 7. Illustration of different configurations of CF-BISAC systems: CF-M-BISAC, CF-B-BISAC and CF-Mlt-BISAC.

3.1. Cell-Free Monostatic BISAC (CF-M-BISAC) Systems

In this configuration, each access point (AP) transmits the ISAC waveform and processes the reflected echoes locally [86–90]. The received signal at the APs contains information of target reflections and backscattered signals, which is locally processed and then combined through cooperative cell-free processing to improve reliability. Synchronization is simplified in these systems owing to the colocated Tx and Rx, enabling low-latency processing and stable sensing operation. Channel estimation and beam training are also simplified as the cascaded channels are locally observed at each AP. The distributed deployment improves coverage uniformity compared to single-node monostatic systems without high inter-node coordination costs. However, colocated transmission and reception at each AP results in strong self-interference which can severely degrade the sensing and BackCom performance of the system.

Although spatial diversity across APs improves reliability, each AP must still maintain a wide dynamic range to improve detection. Cell-free monostatic BISAC systems are well suited for short-range deployments where dense AP placement is feasible and frequent operation is required, e.g., indoor environments, smart factories, and automated warehouses, etc. Here, multiple APs provide localized sensing, tracking, and low-power data transfer while benefiting from cell-free reception diversity. The colocated Tx and Rx enable rapid sensing updates, which are essential for real-time object tracking. The reliance on short-range links aligns with the operational constraints of monostatic backscatter, making these environments ideal for monostatic confirmation.

3.2. Cell-Free Bistatic BISAC (CF-B-BISAC) Systems

In this configuration, transmission and reception is spatially separated across different APs [91–94]. However, a single, dedicated receiving AP is utilized to sense a particular target or receive the backscattered information from the tag [92–94]. A subset of APs illuminates the environment with ISAC waveforms, while other APs collect the reflected echoes from targets and tags [93,94]. By decoupling transmission and reception, bistatic operation avoids full-duplex operation and mitigates self-interference, which reduces energy usage at the AP. The receiver APs can be positioned closer to the region of interest to provide a more effective propagation distance and alleviate the double path-loss effect associated with composite links. This effect cannot be mitigated in the monostatic configuration as the Tx–Rx are colocated.

However, the separation of Tx and Rx complicates synchronization between the APs as each node has independent oscillators. Timing misalignment directly affects sensing precision and backscattered signal processing. Precise coordination is required between the Tx–Rx APs to provide feasible sensing and BackCom performance, which increases channel estimation complexity and imposes tighter requirements on fronthaul latency. These systems are well suited for urban and logistics environments, where distributed AP placement can overcome blockages and extend sensing and communication coverage.

3.3. Cell-Free Multistatic BISAC (CF-Mlt-BISAC) Systems

In this configuration, multiple APs collect reflections from targets and tags and utilize these spatial observation points for multi-perspective sensing and cooperative communication. The resulting spatial diversity significantly improves sensing resolution, parameter estimation, illumination uniformity and communication reliability. Distributed beamforming and joint processing across APs further enhance performance by exploiting spatial diversity.

However, this is achieved at the cost of higher coordination and processing complexity. Accurate synchronization across all participating APs is required to enable coherent and

consistent multi-static observations. Furthermore, each AP observes a distinct cascaded channel, which increases channel estimation overhead and necessitates information exchange over the fronthaul. These requirements exacerbate the processing requirements of the network infrastructure to support real-time operation. This configuration is well-suited for dense urban deployments and vehicular networks requiring reliable, wide-area perception and robust situational awareness.

4. Architectures of CF-BISAC Systems

The architectures of CF-BISAC systems are shown in Figure 8, and summarized in Table 4.

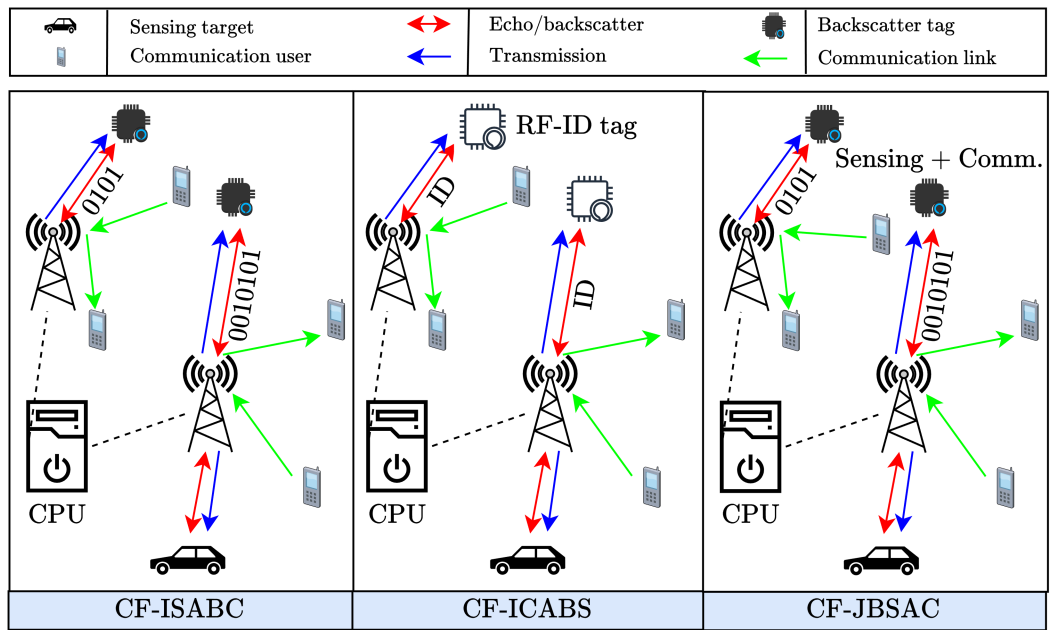


Figure 8. Illustration of different architectures of CF-BISAC systems: CF-ISABC, CF-ICABS and CF-JBSAC.

Table 4. Comparison of different architectures of CF-BISAC systems.

Type of CF-BISAC	CF-ISABC	CF-ICABS	CF-JBSAC
System model	Communication relies exclusively on backscatter links, while sensing is performed using ISAC waveforms.	Conventional uplink/downlink provides communication, while backscatter tags are exploited for sensing functions.	Communication and sensing are jointly realized using the same backscattered waveform.
Role of backscatter	Backscatter is used solely for data transmission.	Backscatter is used solely for identification and sensing.	Backscatter simultaneously supports both communication and sensing functions.
Channel model	Cascaded channel dominates both communication and sensing performance.	Conventional single-hop channels dominate communication, while cascaded channels affect sensing.	Both single-hop and cascaded channels impact sensing and communication.

Table 4. *Cont.*

Type of CF-BISAC	CF-ISABC	CF-ICABS	CF-JBSAC
Sensing capability	Sensing is independent of tag modulation and can realize target detection.	Sensing is tag dependent and enables identification in addition to detection.	Sensing exploits both conventional echoes and tag reflections, enabling identification and detection.
Throughput	Low data-rate BackCom only.	Conventional CF uplink/downlink operation.	Both conventional and tag-based information transfer.
Energy considerations	High energy efficiency, as communication is fully passive.	Tags remain energy efficient, but conventional communication links present.	Joint backscatter sensing and communication has higher illumination requirements.

4.1. Cell-Free Integrated Sensing and Backscatter Communication (CF-ISABC)

In this architecture, the backscatter tags are employed exclusively for passive communication, while sensing targets remain distinct entities. In CF-ISABC, distributed APs illuminate the coverage area with ISAC waveforms which are used to enable sensing and BackCom. This architecture is well suited for systems that prioritize sustainability and minimal power consumption, such as large-scale, battery-free IoT telemetry networks, where ultra-low-power devices transmit low-rate sensor data by modulating incident RF signals. CF-ISABC architectures are also promising for environmental and structural monitoring scenarios, where dense deployments of passive sensors periodically report measurements with minimal maintenance requirements.

The use of distributed APs in this architecture further improves coverage and enables reliable reception of weak backscatter signals which would otherwise be undetectable at a single centralized BS with a larger Tx–Rx distance. However, the energy-rate trade-offs must be considered for efficient and functional system design. Furthermore, dense deployments can result in elevated interference levels, where weak backscattered reflections may be masked by strong direct-path signals.

4.2. Cell-Free Integrated Communication and Backscatter Sensing (CF-ICABS)

CF-ICABS architectures exploit backscatter tags primarily for sensing and identification, while conventional uplink and downlink transmissions support communication. This architecture can enable target identification in addition to target detection functions. In this configuration, backscatter tags replace conventional ISAC targets by embedding identification information into reflected RF signals. When tags are mounted on the objects of interest, CF-ICABS systems enable identification of the device-based targets, as the reflected signals simultaneously carry tag identity and sensing parameters such as location, range, or velocity. The use of distributed APs allows multiple spatial observations of tag reflections, which improves identification reliability and sensing accuracy without increasing spectrum usage or transmit power.

CF-ICABS architecture is promising for logistics, inventory management, and asset tracking applications, where both identification and localization are required over large areas. However, since sensing relies on tag-modulated reflections, parameter estimation becomes sensitive to tag modulation. Maintaining alignment between tag modulation and sensing processing across distributed APs introduces additional coordination requirements, which increases processing complexity and overhead.

4.3. Cell-Free Joint Backscatter-Enabled Sensing and Communication (CF-JBSAC)

In this architecture, the backscatter tags are utilized to simultaneously transmit information and provide parameter estimation for environmental information. The conventional device-free targets and backscatter tags are both utilized as objects of interest for the sensing system. Similarly, conventional uplink/downlink users and backscatter tags are used for information transfer. This drastically improves spectral efficiency and energy efficiency by avoiding dedicated probing waveforms.

Distributed APs are a key enabler of this architecture, since conventional centralized systems suffer from large Tx–Rx distances that severely attenuate weak backscatter reflections and limit reliable joint sensing and communication. These are well-suited for intelligent infrastructure and smart transportation systems, where passive roadside units (RSU) can enable vehicle-to-infrastructure communication alongside real-time sensing. However, the coupling between sensing and communication functions exacerbates the synchronization requirements of the system, which increases computational complexity and complicates energy efficiency. Furthermore, receivers must operate over a wide dynamic range to reliably detect weak backscattered echoes in the presence of strong illuminating signals.

5. Challenges of CF-BISAC Systems

The challenges of CF-BISAC systems are delineated in this section.

5.1. Doppler Effects in High Mobility Scenarios

In wireless systems, Doppler effects arise from the relative motion between transceivers, targets, and scatterers, which results in frequency shifts and time-selective channels [95]. As most sensing applications demand mobile object tracking and monitoring, these effects can have more impact in ISAC systems. They can directly impact channel estimation, beamforming, and the precision of parameter estimation of mobile targets. In CF-BISAC systems, Doppler effects are more challenging compared to conventional ISAC systems owing to the distributed nature of the APs [96]. Each AP experiences a distinct Doppler shift due to the relative motion from different spatial localities. They can severely affect the decoding of weak backscattered signals in CF-BISAC systems. Furthermore, Doppler shifts affect both the forward path and the backscattered path, which exacerbates the time-selectivity of the effective channel. This is critical in high-mobility scenarios such as vehicular sensing, unmanned aerial vehicles (UAV)-assisted networks, and industrial automation where moving machinery must be monitored in real time. The estimation and modeling of Doppler shifts is significant for feasible sensing and communication performance. Doppler mismatches can severely degrade net system performance and cause errors in sensing parameter estimation. In addition, Doppler-induced channel variations severely complicate the demodulation and detection of weak backscattered signals. These effects are more pronounced under low SNR conditions and strong direct-link interference, leading to high error rates in tag information recovery. Doppler-aware channel estimation [97,98], Doppler-aware scheduling [99] and mobility-adaptive beamforming [100] can be utilized to mitigate these effects. However, the mitigation of these effects in dynamic CF-BISAC systems remains an open challenge.

5.2. Beam-Split Effect in Wideband Systems

In wideband systems, the beam-split effect causes different frequency components to focus and align towards different spatial directions, resulting in angular and range misalignment across the signal bandwidth [101,102]. This results in reduced array gain which consequently degrades the sensing and communication signal-to-interference-plus-noise

ratio (SINR). In CF-BISAC systems, each AP forms beams independently, and frequency-dependent beam misalignment accumulates across the network during cooperative processing. For backscattered signals, this results in non-uniform illumination and distorted sensing estimates. This is critical in millimeter wave (mmWave) systems where large bandwidths are required to achieve high sensing resolution and improved data rates. Performance degradation is particularly exacerbated for cascaded backscatter channels, as they rely on precise beam focusing to recover weak reflections. True-time-delay (TTD) beamforming [103], sub-band-based beamforming [104], and beam-split aware precoding/combining [105] can be utilized to mitigate these effects.

5.3. Channel Reciprocity and Channel Calibration

Channel reciprocity refers to the assumption that uplink and downlink propagation channels are identical in wireless systems. In cell-free architectures, this assumption is challenging as many distributed APs must simultaneously realize reciprocity, each with independent and non-reciprocal RF hardware chains [106,107]. In CF-BISAC systems, channel calibration is significantly more challenging as reciprocity must be preserved across a large number of spatially distributed APs, and both sensing and BackCom have cascaded two-way channels, which are sensitive to estimation errors. Hardware mismatches and timing misalignment across different APs introduce phase and amplitude inconsistencies in CSI estimates, which distorts the effective cascaded channels and drastically decreases the net system performance. These errors directly degrade beamforming gain and reduce interference suppression across the CF-BISAC network. Distributed calibration techniques can mitigate these challenges [25,107].

5.4. Synchronization of Distributed Access Points

Synchronization in time, frequency, and phase across multiple APs is required to realize high beamforming gains, efficient information decoding and precise parameter estimation. In CF-BISAC systems, synchronization is highly challenging as APs are geographically separated and operate with independent clocks and oscillators [108]. Timing or carrier frequency offsets can directly impact the joint observation of backscatter signals and target echoes. Furthermore, the performance gains of CF-BISAC systems rely on coherent combining. Minor errors in synchronization can result in destructive signal combining, and drastically degrade sensing and communication performance. These challenges are exacerbated by the large-scale MIMO dimensions which arise from numerous distributed APs, users, and tags. They result in extremely large channel matrices and signal models, which significantly increase signal processing and coordination complexity.

5.5. Fronthaul Capacity

Fronthaul and backhaul links connect distributed APs to the CPU and support the exchange of information required for cooperative communication and sensing [109,110]. In CF-BISAC systems, these links not only carry conventional control signals, but also transfer channel information and processed baseband signal information extracted from the signals received at APs [111]. The volume of data increases significantly with the number of APs, sensing targets, communication users, and tags. This is exacerbated when raw or baseband processed signals are forwarded to realize cooperative beamforming and aggregated processing. The transmission of large-dimensional MIMO channel matrices, target reflections and backscatter signals over the fronthaul links significantly increases system latency and computational complexity. Limited fronthaul or excessive latency can have drastic effects on the performance of CF-ISABC systems. Hierarchical processing architectures can be employed to mitigate these challenges where partial sensing or processing is realized on distributed APs before forwarding the extracted information to the CPUs. Compressed

information exchange, hierarchical processing [112] and task-oriented data sharing can reduce processing load while sustaining effective operation.

6. Future Directions of CF-BISAC Systems

The prospective future directions which mitigate the challenges of CF-BISAC systems are discussed in this section. The overview is given in Figure 9.

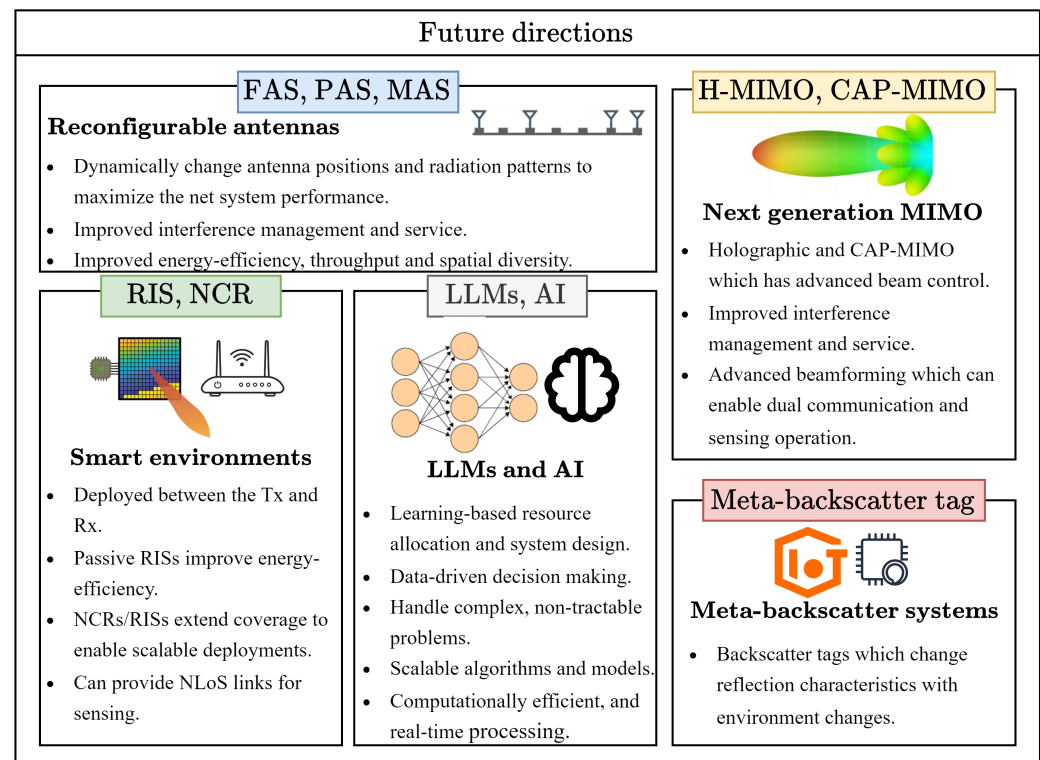


Figure 9. Future directions in CF-BISAC systems: Reconfigurable antennas, next generation MIMO, smart environments, LLMs, AI and meta-backscatter systems.

6.1. Smart Environments

In next-generation systems, researchers are exploring technologies to actively control the propagation medium between the transmitters and the receivers. This is done to compensate for the severe path loss, blockage, clutter and shadowing effects, hence, improving received signal power, coverage uniformity, and sensing precision. Reconfigurable intelligent surfaces (RISs) and network-controlled repeaters (NCRs) are emerging as two promising candidate solutions for smart environments. RISs are deployed between the transmitter and the receiver, and actively configure the propagation channel to realize a virtual LoS link for maximal signal reception at the receiver [113–117]. NCRs are smart relays which amplify-and-forward the signal to mitigate blockages and clutter while applying beamforming on both reception and transmission using network information, thus improving overall system performance.

In CF-BISAC systems, RISs increase the probability of LoS reception and NCRs reduce the effective link distances to improve system performance. This is particularly relevant for BackCom, since weak signal components compete against strong direct-path signals for detection and decoding. However, smart environments introduce system-level constraints which are specific to CF-BISAC systems. NCRs amplify noise and interference in addition to desired signals, which necessitate advanced interference management algorithms for

feasible operation. RISs do not amplify noise, but they require configuration of reflection coefficients, which creates an additional computation burden.

6.2. Reconfigurable Antenna Technologies

The stringent demands of next-generation systems have motivated the exploration of reconfigurable antenna technologies which extend the concept of spatial diversity by enabling dynamic control over the physical position or effective aperture of antenna elements to enable dynamic reconfiguration of antenna radiation characteristics [118–123]. Technologies such as fluid antennas [118,119,124,125], moving antennas [120,121,126,127], and pinching antennas [122,123,128,129] are emerging as the practical realizations of reconfigurable antennas. They provide additional spatial degrees of freedom which adapt to channel conditions by reshaping the antenna geometry in real time [118–123]. Their reconfigurability is motivating their inclusion in ISAC systems [130–137]. In CF-BISAC systems, reconfigurable antennas can enhance reception performance at distributed access points and conventional downlink/uplink users by reconfiguring the antennas with dominant propagation paths. By adjusting antenna positions or effective apertures, reconfigurable antennas improve the detection of weak backscattered reflections and enhance the signal-to-noise ratio at the receiver. This leads to improved sensing reliability and communication performance without increasing transmit power. On the user or receiver side, reconfigurable antennas mitigate channel fading and improve net system energy efficiency by reducing the need for excessive illumination or retransmissions. For systems with centralized illumination and cell-free receivers, reconfigurable antennas can compensate for deep fades and blockages by dynamically adjusting their spatial configuration to maximize received signal power.

Despite these benefits, the integration of reconfigurable antennas makes channel state information retrieval more challenging. Owing to the continuously changing antenna geometry, the effective channel response varies, and requires frequent acquisitions. Furthermore, to realize the performance gains of reconfigurable antennas, joint optimization of antenna positions, radiation patterns, and signal processing parameters is required, which leads to high-dimensional and non-convex optimization problems. These challenges increase computational complexity and require efficient control and learning-based algorithms to enable practical real-time operation in CF-BISAC systems.

6.3. Meta-Backscatter Systems

The latest research in backscatter-aided ISAC systems is employing meta-backscatter tags as passive devices whose reflection characteristics vary with physical or environmental conditions [62,138–141]. These tags are typically fabricated using metamaterials composed of sub-wavelength elements, whose frequency responses are highly sensitive to environmental parameters such as temperature, pressure, and humidity. As a result, variations in environmental conditions can be directly encoded into the reflection coefficients of the tags, hence modulating the properties of the backscattered signals. This capability enables meta-backscatter systems to realize a battery-free sensing network, making them highly suitable for large-scale and long-term IoT deployments.

In CF-BISAC systems, meta-material tags can have uniform illumination which provides real-time monitoring capabilities and improves sensing reliability and robustness compared to centralized reception. Unlike conventional ISAC systems that rely on signal reflections from objects of interest to estimate target parameters, meta-backscatter tags couple physical properties of the sensing target directly onto the reflected signal. Sensing receivers extract sensing information by processing the changes in the spectral characteristics of the received signal. The integration of meta-backscatter tags with CF-BISAC is promising ow-

ing to the extended coverage and feasible Tx–Rx distances which have uniform illumination, even in blocked and cluttered environments. However, the frequency-selective reflection of meta-materials alters the effective channel response, which complicates channel estimation and signal processing.

6.4. Large Language Models (LLMs) and Artificial Intelligence (AI)

AI-based signal processing is emerging as a key enabler for next-generation systems owing to the stringent, versatile demands of 6G networks [142–147]. In CF-BISAC systems, the high-dimensional sensing, communication, and coordination tasks further motivate the inclusion of AI in system design. Conventional model-based optimization becomes increasingly complex in cell-free deployments with owing to the dynamic environments, channel estimation complexity and distributed APs. LLMs and AI provide a data-driven mechanism for optimizing system-level design variables which can maximize sensing and communication performance. In CF-BISAC systems, AI models can enable distributed resource allocation [142–144], AP selection [145–147], fronthaul/backhaul management, channel estimation, beamtraining/beamforming and parameter tuning. These models can mitigate mobility, blockage, channel estimation and clutter challenges by learning correlations across time, space, and frequency. Centralized or hierarchical AI architectures can be deployed at the CPU to aggregate distributed observations and control network-wide processing without requiring explicit analytical models for all propagation effects. This can improve scalability in complex environments by supporting adaptive sensing–communication trade-offs.

6.5. Next-Generation MIMO

Next-generation MIMO technologies, e.g., holographic MIMO and continuous aperture (CAP) MIMO, extend beyond conventional discrete antenna arrays to enable advanced beam and improve spatial resolution, beamforming and interference management [148–153]. This is motivating their exploration for ISAC systems [154–157]. Holographic MIMO employs ultra-dense antenna placement with sub-wavelength element spacing to approximate a continuous electromagnetic aperture [148–150]. This enables ultra-fine spatial control of radiated and received wavefronts, supporting near-field beam focusing and spatial multiplexing beyond conventional discrete-array beamforming. In CF-BISAC systems, holographic MIMO can improve the detection and separability of backscattered and reflected signals by providing a large effective aperture. It also enables the exploitation of spherical-wave propagation, which can simultaneously provide angular and range information, thus improving the sensing performance of the system. CAP MIMO technologies model the antenna system as a continuous radiating surface instead of a finite set of elements [151–153]. In CF-BISAC systems, CAP-MIMO supports efficient extraction of weak backscatter components by increasing effective aperture size without relying on extremely large colocated arrays. While next-generation MIMO technologies enhance sensing accuracy and improve spatial separation between direct-path and backscattered signals, they can impose hardware scalability constraints. They can also have higher channel calibration and estimation costs, which must realize a trade-off with energy efficiency.

These research directions improve energy efficiency of CF-BISAC systems primarily by reducing illumination requirements, mitigating signal degradation, and improving resource utilization across distributed access points. Smart environments and reconfigurable antennas enhance link reliability and reception quality, which consequently lowers transmission power and retransmission overhead. Meta-backscatter systems enable energy-efficient sensing by directly encoding physical information into passive reflections, supporting large-scale low-power deployments. Next-generation MIMO architectures improve spatial

resolution and signal detection, enabling more efficient extraction of weak backscattered signals with reduced processing cost. AI and LLM-based frameworks enable adaptive coordination and resource management, which limits the energy usage caused by mobility, blockage, and channel uncertainty. Together, these technologies can be integrated to improve the system-level energy efficiency and scalability of CF-BISAC systems.

7. Conclusions

This article delineated the potential of CF-BISAC systems as an enabler for next-generation ISAC systems. We bridged cell-free MIMO and backscatter technologies and provided a thorough discussion of the fundamental principles, system architectures, configurations, and energy efficiency considerations of CF-BISAC systems. The different architectures and configurations of CF-BISAC systems were discussed alongside the key opportunities, technical challenges, and performance trade-offs. We then discussed the major challenges associated with the practical deployments of CF-BISAC systems. Furthermore, emerging directions such as meta-backscatter systems, reconfigurable antenna technologies, smart environments, and AI were discussed to support sustainable and scalable IoT deployments. This work established an energy-centric perspective for the future development of CF-BISAC systems, and highlighted their relevance to IoT applications of next-generation wireless architectures.

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