

# Advancements in UAV-Based Integrated Sensing and Communication: A Comprehensive Survey

MANZOOR AHMED<sup>1,2</sup> (Member, IEEE), SYED TARIQ SHAH<sup>3</sup>, ALI ARSHAD NASIR<sup>4,5</sup>,  
MUDASSIR MASOOD<sup>4,5</sup> (Senior Member, IEEE), KAMRAN ALI MEMON<sup>6</sup>,  
KHURRAM KARIM QURESHI<sup>4,5</sup>, FEROZ KHAN<sup>7</sup>, WALI ULLAH KHAN<sup>8</sup>, AHMAR SHAFI<sup>4,5</sup>,  
FANG XU<sup>1</sup>, AND ZHU HAN<sup>9</sup> (Fellow, IEEE)

<sup>1</sup>School of Computer and Information Science, Hubei Engineering University, Xiaogan 432000, China

<sup>2</sup>Institute for AI Industrial Technology Research, Hubei Engineering University, Xiaogan 432000, China

<sup>3</sup>School of Computer Science and Electronic Engineering, University of Essex, Colchester CO4 3SQ, U.K

<sup>4</sup>Interdisciplinary Research Center for Communication Systems and Sensing, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia

<sup>5</sup>Department of Electrical Engineering, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia

<sup>6</sup>Department of Electrical Engineering, Prince Mohammad Bin Fahd University, Al Khobar 31952, Saudi Arabia

<sup>7</sup>School of Electronic Engineering, Beijing University of Posts and Telecommunications, Beijing 100876, China

<sup>8</sup>School of Computing, Gachon University, Seongnam-si, Gyeonggi-do 13120, South Korea

<sup>9</sup>Department of Electrical and Computer Engineering, University of Houston, Houston, TX 77004 USA

CORRESPONDING AUTHORS: S. T. SHAH (syed.shah@essex.ac.uk) AND W. U. KHAN (waliullahkhan30@gmail.com)

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**ABSTRACT** Uncrewed aerial vehicles (UAVs) integrated with integrated sensing and communication (ISAC) technology have emerged as a compelling platform for sixth-generation (6G) wireless networks, leveraging three-dimensional mobility to perform simultaneous sensing and communication (S&C) across applications ranging from disaster response to airspace monitoring. While the field has advanced rapidly, existing surveys have not sufficiently characterized UAV-specific design challenges nor the cross-cutting trade-offs governing practical deployment. To bridge this gap, this survey provides a systematic review across six interconnected domains—channel estimation (CE) and beam tracking, throughput maximization, weighted sum rate (WSR) and sensing co-optimization, delay and age of information (AoI) minimization, energy efficiency (EE), and PLS—each supported by a structured comparative table covering over 80 methodologies. The survey concludes with a research roadmap addressing propagation modeling, platform dynamics, imperfect channel state information (CSI) robustness, energy-AoI-security co-design, and standardization, providing a structured foundation for future 6G UAV-ISAC research.

**INDEX TERMS** 6G, ISAC, UAVs, sensing and communication, channel estimation, MEC, AI, and DRL.

## I. INTRODUCTION

WITH the emergence of sixth-generation (6G) wireless networks, communication systems are poised to reshape and offer unprecedented data rates, ultra-low latency, and pervasive connectivity. Hence, enabling transformative applications such as holographic communications, deeply integrated artificial intelligence (AI), and seamless Internet of Everything (IoE) services [1], [2], [3], [4], [5], [6]. 6G era is characterized by the adoption of terahertz (THz) bands, advanced massive multiple-input multiple-output (mMIMO), reconfigurable intelligent surfaces (RIS) [7], and integrated sensing and communication (ISAC) networks [8].

ISAC has emerged as a disruptive technology that plays an essential role in the next generation wireless systems,

particularly 6G networks [9], [10], [11]. This paradigm unifies sensing and communication (S&C) functions by sharing common resources that include hardware, spectrum, and energy. Thereby achieving high-efficiency operation at lower costs and promoting sustainability [12], [13]. In contrast, conventional architectures employ separate S&C modules that lead to higher energy consumption, additional spectrum usage, and increased deployment costs caused by duplicated hardware interfaces [14]. By jointly realizing S&C within a unified framework, ISAC alleviates these drawbacks, enhancing energy efficiency (EE) and spectral efficiency (SE) while reducing hardware redundancy [15], [16]. Thanks to these benefits, ISAC has been widely investigated in terrestrial networks, non-terrestrial net-

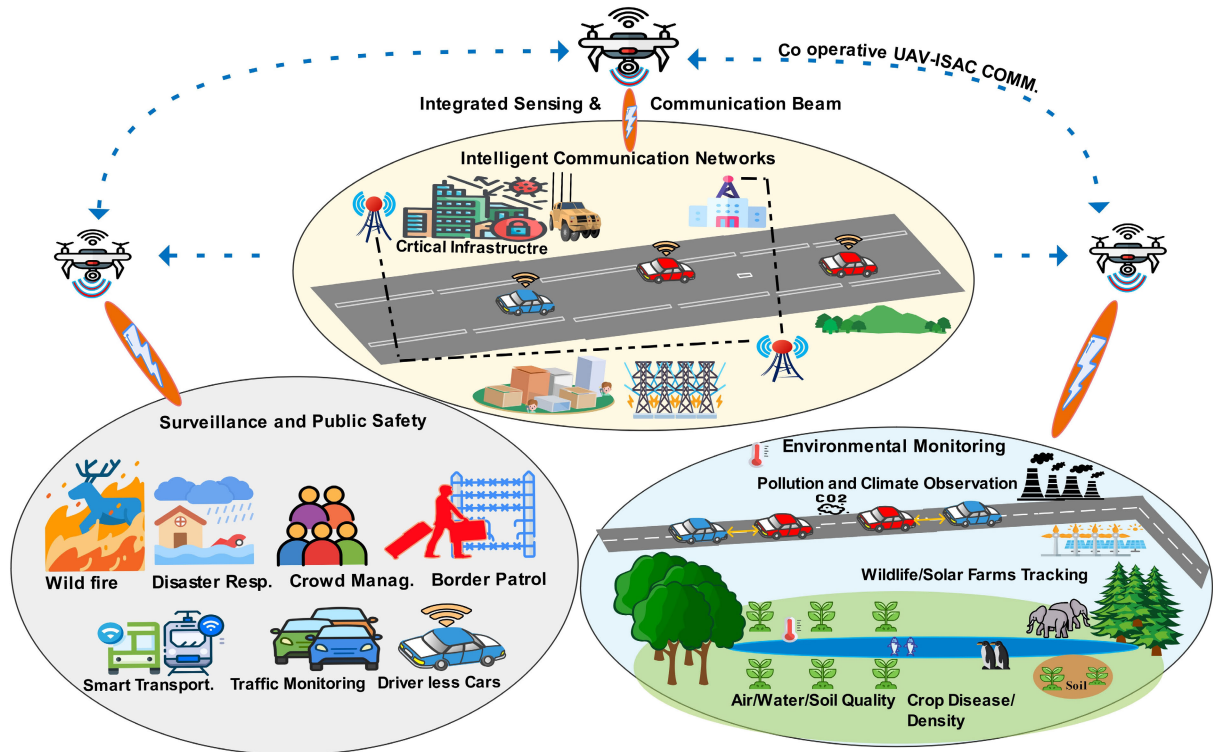


FIGURE 1. Applications of UAV-based ISAC systems in diverse scenarios.

works, and hybrid architectures that integrate both domains [17], [18].

The fundamental idea of ISAC is the tight coupling between S&C, so that each function enhances the other and yields richer system capabilities. This integration manifests in two complementary directions. On the one hand, sensing-aided communication exploits real-time environmental information, such as obstacle locations and channel state information (CSI), to improve link reliability, coverage, and throughput. On the other hand, communication-assisted sensing leverages existing network infrastructure to support distributed measurements, multi-source data fusion, and coordinated operations across multiple nodes. This interaction not only expands the system's overall functionality but also introduces new design degrees of freedom, enabling innovative applications and more efficient utilization of spectral, energy, and hardware resources [19].

Uncrewed aerial vehicles (UAVs) have emerged as a particularly promising platform for ISAC implementation, as their aerial mobility provides distinctive advantages for integrated S&C operations [20], [21]. UAV-enabled ISAC systems enable collaborative functionality and simultaneous S&C execution through shared use of both spectral and hardware resources. This capability ultimately overcomes the limitations of conventional ground-based infrastructure [22]. Unlike fixed terrestrial systems, UAVs possess the unique ability to maneuver freely in three-dimensional space, allowing them to circumvent obstacles that would otherwise block line-of-sight (LoS) links [23], [24]. This operational flexibility translates to both robust communication connectivity

and highly accurate sensing performance, even in challenging environments such as remote areas, dense urban settings, and disaster zones where conventional infrastructure may be unavailable, damaged, or insufficient.

UAV's mobility significantly enhances the flexibility of ISAC systems, making them suitable for S&C operations and performance [21], [25]. This enables additional degrees of freedom (DoF) to the system design and accordingly makes UAV-ISAC systems for high-responsiveness applications [26]. Such systems have found applications in intelligent communication networks, autonomous systems, humanitarian assistance/disaster recovery operations, surveillance, and public safety problems, as depicted in Fig. 1.

The development of near-field ISAC (NF-ISAC), which is based on the utilization of massive antenna arrays, has recently opened new venues for high-resolution sensing and accurate beam control by assuming spherical wave propagation [27], [28]. Integrating UAVs with NF-ISAC systems presents particularly promising prospects, as their mobility and proximity to ground users make them ideal for localized operations. This configuration provides superior spatial resolution, low latency communication, and better multi-target tracking, capabilities that are highly desirable in emerging applications urban air mobility and aerial surveillance [29], [30]. Although research on UAV-based NF-ISAC remains in its early stages, it is anticipated to become a key enabling technology for future 6G wireless systems.

UAV-ISAC systems balance flexibility and agility to manage critical performance trade-offs in next-generation wireless networks [31], [32]. These are trade-offs between

TABLE 1. Summary of important acronyms.

| Abbreviation | Definition                                   |
|--------------|----------------------------------------------|
| 6G           | Sixth Generation                             |
| AI           | Artificial Intelligence                      |
| AO           | Alternate Optimization                       |
| AoA          | Angle of Arrival                             |
| AoD          | Angle of Departure                           |
| AoI          | Age of Information                           |
| B5G          | Beyond 5th Generation                        |
| BCD          | Block Coordinate Descent                     |
| BS           | Base Station                                 |
| CE           | Channel Estimation                           |
| CNN          | Convolutional Neural Network                 |
| CRB          | Cramér-Rao Bound                             |
| CSI          | Channel State Information                    |
| DDPG         | Deep Deterministic Policy Gradient           |
| DFRC         | Dual Function Radar Communication            |
| DoA          | Direction of Arrival                         |
| DRL          | Deep Reinforcement Learning                  |
| EE           | Energy Efficiency                            |
| EKF          | Extended Kalman Filter                       |
| Eve          | Eavesdropper                                 |
| GUE          | Ground User Equipment                        |
| HAP          | High Altitude Platform                       |
| IoT          | Internet of Things                           |
| ISAC         | Integrated Sensing and Communication         |
| LAE          | Low-Altitude Economy                         |
| LLM          | Large Language Model                         |
| LoS          | Line of Sight                                |
| LSTM         | Long Short-Term Memory                       |
| MDP          | Markov Decision Process                      |
| MEC          | Multi-access Edge Computing                  |
| ML           | Machine Learning                             |
| NF           | Near Field                                   |
| NLoS         | Non-Line-of-Sight                            |
| NOMA         | Non-Orthogonal Multiple Access               |
| NTNs         | Non-Terrestrial Networks                     |
| PLS          | Physical Layer Security                      |
| PPO          | Proximal Policy Optimization                 |
| PSO          | Particle Swarm Optimization                  |
| RHS          | Reconfigurable Holographic Surfaces          |
| RIS          | Reconfigurable Intelligent Surfaces          |
| RL           | Reinforcement Learning                       |
| S&C          | Sensing and Communication                    |
| SCA          | Successive Convex Approximation              |
| SCE          | Secure Computation Efficiency                |
| SDR          | Semidefinite Relaxation                      |
| SNR          | Signal-to-Noise Ratio                        |
| SOP          | Secrecy Outage Probability                   |
| SR           | Sum Rate                                     |
| STAR-RIS     | Simultaneous Transmission and Reflection RIS |
| THz          | Terahertz                                    |
| UAV          | Unmanned Aerial Vehicle                      |
| V2X          | Vehicle-to-Everything                        |
| WPT          | Wireless Power Transfer                      |
| WSR          | Weighted Sum Rate                            |
| XLAA         | Extremely Large Antenna Arrays               |

the weighted sum rate (WSR) and S&C, trade-off between optimizing throughput with joint S&C constraints, minimizing latency and AoI, improving EE, and guaranteeing secure operation in dynamic network conditions. UAV-enabled dynamic position reconfigurations provides an effective countermeasure against interference and eavesdropping threats. This capability is essential for maintaining resilient and secure communication in reliability-critical applications such as military surveillance, disaster recovery, and various other similar applications [33].

## A. RELATED SURVEYS

To ensure transparent and reproducible coverage, we adopted a structured selection protocol rather than an ad hoc literature scan. We queried IEEE Xplore, ScienceDirect, and arXiv using combinations of the terms “UAV,” “drone,” or “aerial”

with “integrated sensing and communication,” “ISAC,” “joint sensing and communication,” or “dual-function radar-communication,” and supplemented these with backward and forward citation tracing from the most-cited works in each of the six domains. The primary time-frame was 2021–2026, reflecting the period over which UAV-specific ISAC designs emerged as a distinct body of work, with a small number of foundational pre-2021 references retained for conceptual completeness (e.g., DFRC and radar-communication coexistence fundamentals). A work was included if it (i) addressed a UAV-based or UAV-assisted ISAC system rather than generic terrestrial ISAC, and (ii) contributed an identifiable design, algorithm, analytical framework, or performance characterization mappable to at least one of the six domains in our taxonomy. We excluded works that treated UAVs purely as communication relays without a sensing function, those addressing sensing or communication in isolation, and short abstracts or posters lacking sufficient methodological detail for tabular comparison. We sought comprehensive coverage of the works satisfying these criteria and also included recently appeared 2026 contributions to keep the coverage current.

As summarized in Table 2, ISAC is widely regarded as a disruptive technology with significant potential to shape future wireless networks. A number of existing surveys have explored its advancements, challenges, and practical applications to map its capabilities. The literature underscores the vital role of ISAC in the Internet of Things (IoT), where studies demonstrate its importance for creating seamlessly integrated systems with enhanced performance metrics [34]. From a theoretical standpoint, other works have delved into the fundamental performance limits of ISAC, analyzing the inherent trade-offs between sensing and communication functions to identify effective balancing strategies [35]. Recent classifications of ISAC waveform design, categorizing approaches as communication-centric, sensing-centric, or jointly optimized, provide a structured framework that informs the development of next-generation systems [36].

Within vehicular networks, ISAC has emerged as a pivotal research area, offering solutions to critical demands for low-latency links, precise localization, and autonomous navigation. Research in this domain confirms that integrated sensing and communication is indispensable for future transportation, promising substantial gains in safety, efficiency, and accuracy [37], [38]. Similarly, ISAC systems leveraging UAVs are gaining attention for their inherent mobility and flexibility, making them highly suitable for deployment in complex and unpredictable settings [39].

The exploration of ISAC for 5G-Advanced and 6G networks focuses heavily on signal design and system optimization. Contemporary studies explore waveform optimization and energy-efficient protocol design as key enablers of performance improvement [40]. Another major trend is the application of machine learning (ML), enabling data-driven advances in areas like user localization, adaptive beamform-

**TABLE 2.** Survey papers’ comparison related to UAV-based ISAC.

| Ref.                                           | Year | Focus of the Related Surveys                                                                                                                                                                                                                                                                                                                                                                                                                                                                        | CE/Target and Beam Tracking | System Throughput | WSR and Sensing | Delay | EE  | Security |
|------------------------------------------------|------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------|-------------------|-----------------|-------|-----|----------|
| Prior Surveys on ISAC and Related Technologies |      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     |                             |                   |                 |       |     |          |
| [34]                                           | 2021 | Highlights ISAC’s role in enabling seamless IoT applications                                                                                                                                                                                                                                                                                                                                                                                                                                        | ×                           | ×                 | ×               | ×     | ×   | ×        |
| [35]                                           | 2022 | Explores the theoretical trade-offs and performance limits of ISAC systems                                                                                                                                                                                                                                                                                                                                                                                                                          | ×                           | ×                 | ×               | ×     | ×   | ×        |
| [36]                                           | 2022 | Explores joint waveform design to balance ISAC sensing and communication requirements                                                                                                                                                                                                                                                                                                                                                                                                               | ×                           | ×                 | ×               | ×     | ×   | ×        |
| [37]                                           | 2022 | Discusses ISAC’s potential in enabling advanced vehicular networks                                                                                                                                                                                                                                                                                                                                                                                                                                  | ×                           | ×                 | ×               | ×     | ×   | ×        |
| [38]                                           | 2025 | Highlights ISAC as a solution in CAV networks’ challenges, focusing on application and advancements for 6G                                                                                                                                                                                                                                                                                                                                                                                          | ×                           | ×                 | ×               | ×     | ×   | ×        |
| [39]                                           | 2024 | Highlights UAVs’ role in ISAC for real-time adaptability and sensing flexibility                                                                                                                                                                                                                                                                                                                                                                                                                    | *                           | ×                 | ×               | ×     | *   | ×        |
| [40]                                           | 2023 | Focuses on signal design and optimization for ISAC in 5G-A and 6G                                                                                                                                                                                                                                                                                                                                                                                                                                   | ×                           | ×                 | ×               | ×     | ×   | ×        |
| [41]                                           | 2025 | Highlights data-driven approaches for enhancing ISAC efficiency and accuracy                                                                                                                                                                                                                                                                                                                                                                                                                        | *                           | ×                 | ×               | ×     | *   | ×        |
| [42]                                           | 2024 | Highlights machine learning’s role in improving ISAC sensing, communication, and resource allocation                                                                                                                                                                                                                                                                                                                                                                                                | *                           | ×                 | ×               | ×     | *   | ×        |
| [43]                                           | 2024 | Explores advancements from the collaboration of sensing, communication, and AI                                                                                                                                                                                                                                                                                                                                                                                                                      | *                           | ×                 | ×               | ×     | ×   | ×        |
| [44]                                           | 2024 | Focuses on channel modeling approaches and opportunities for ISAC in 6G networks                                                                                                                                                                                                                                                                                                                                                                                                                    | ***                         | ×                 | ×               | ×     | ×   | ×        |
| [45]                                           | 2024 | Outlines a vision for ISAC networks; explores signal processing, optimization, and ML techniques within the 6G framework                                                                                                                                                                                                                                                                                                                                                                            | ***                         | ×                 | ×               | ×     | *   | ×        |
| [46]                                           | 2025 | Examines the integration of sensing, communication, and computation in next-generation networks                                                                                                                                                                                                                                                                                                                                                                                                     | *                           | *                 | ×               | ×     | *   | **       |
| [47]                                           | 2025 | Discusses strategies for mitigating interference in ISAC systems                                                                                                                                                                                                                                                                                                                                                                                                                                    | ×                           | ×                 | ×               | ×     | ×   | ×        |
| [48]                                           | 2024 | Highlights OTFS modulation’s role in improving ISAC SE                                                                                                                                                                                                                                                                                                                                                                                                                                              | ×                           | ×                 | ×               | ×     | ×   | ×        |
| [49]                                           | 2024 | Focuses on enhancing security and privacy in ISAC systems                                                                                                                                                                                                                                                                                                                                                                                                                                           | ×                           | ×                 | ×               | ×     | ×   | ***      |
| [50]                                           | 2024 | Highlights the potential and challenges of using THz frequencies for ISAC                                                                                                                                                                                                                                                                                                                                                                                                                           | ×                           | ×                 | ×               | ×     | ×   | ×        |
| [51]                                           | 2025 | Highlights the role of metasurfaces in enhancing ISAC efficiency and adaptability                                                                                                                                                                                                                                                                                                                                                                                                                   | *                           | ×                 | *               | ×     | *   | *        |
| This Survey                                    |      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     |                             |                   |                 |       |     |          |
| Our                                            | 2026 | We present a systematic review of UAV-ISAC, which comprises of six domains supported by structured comparative tables (Tables III–VIII) covering >80 methodologies: CE/beam tracking (Table III, 16 works); system throughput (Table IV, 26 works); WSR-sensing co-design (Table V, 15 works); delay and AoI (Table VI, 8 works); EE (Table VII, 16 works); PLS (Table VIII, 18 works, three threat categories). Cross-cutting design principles and open challenges are synthesized in Section IV. | ***                         | ***               | ***             | ***   | *** | ***      |

Coverage criteria (× Not Covered; \* Preliminary <0.5 pages; \*\* Partial, no comparative table; \*\*\* Full: dedicated subsection + comparative table + cross-paper synthesis). Ratings for prior surveys assigned independently based on content of each reference.

ing, and resource allocation, thereby boosting the efficiency of modern ISAC networks [41], [42]. More broadly, artificial intelligence (AI) is emerging as a central enabler for achieving scalable, optimized, and dynamically adaptive ISAC systems [43].

Research into 6G-ISAC also identifies persistent challenges, such as sophisticated interference management, dynamic spectrum sharing, and dealing with non-stationary wireless channels. Proposed solutions often involve advanced beamforming and hybrid system architectures to bolster operational efficiency [44]. The applicability of ISAC is further evidenced by its integration into smart city infrastructure and autonomous systems, highlighting its relevance for next-generation use cases [45].

Furthermore, the deep integration of sensing, communication, and computation is also emphasized as a critical requirement for real-time resource management in future 6G applications [46]. To mitigate performance degradation in dense networks, novel interference management strategies

are being developed specifically for ISAC deployments [47]. Modulation schemes such as Orthogonal Time-Frequency Space (OTFS) have also been studied for their robustness and high spectral efficiency in high-mobility scenarios [48]. Despite the technological progress, security and privacy concerns present significant hurdles for widespread ISAC adoption [49]. Concurrently, the use of Terahertz (THz) frequencies is being explored, which, despite challenges like severe path loss and complex beam management, offer immense potential for high-capacity ISAC links [50]. A growing body of research explores the synergy between ISAC and intelligent metasurfaces, where reconfigurable intelligent surfaces (RIS) dynamically control electromagnetic waves to enhance spectral efficiency, adaptability, and overall performance [51]. Collectively, these surveys provide a multifaceted perspective on ISAC’s opportunities and obstacles, establishing a foundational knowledge base for its implementation in advanced wireless networks.

## B. MOTIVATION

The vision for 6G networks necessitates a seamless fusion of sensing and communication to enable transformative applications—from autonomous smart cities and precision agriculture to rapid disaster response and airspace monitoring. Conventional terrestrial ISAC systems, however, are constrained by static infrastructure that frequently suffers from line-of-sight (LoS) obstructions, limited spatial adaptability, and inefficient resource utilization in geographically complex or rapidly changing environments.

UAV-based ISAC presents a paradigm shift. By exploiting inherent three-dimensional mobility, UAVs can establish on-demand LoS links, dynamically reposition to optimize shared spectrum and hardware resources, and achieve high-resolution sensing from advantageous aerial vantage points—capabilities that collectively address the coverage, efficiency, and adaptability gaps left by ground-based deployments. Yet as Table 2 reveals, existing surveys treat UAV-ISAC either as a peripheral application of broader ISAC frameworks or focus narrowly on individual aspects such as channel modeling or security, without synthesizing the unique technical challenges that aerial mobility introduces. Specifically, no prior survey has jointly characterized the interactions among jitter-resilient channel estimation, control-aware trajectory optimization, sensing metric selection, algorithm scalability, and physical layer security (PLS) within a unified UAV-ISAC framework. This survey bridges that gap.

## C. CONTRIBUTIONS

Motivated by the research gaps identified above, this survey makes the following interconnected contributions:

- 1) **UAV-ISAC Foundational Framework:** We establish the fundamental principles of UAVs and ISAC and analyze why their integration is uniquely suited to 6G requirements. This includes a characterization of UAV roles—airial base station (BS), relay, and transceiver—alongside monostatic, bistatic, and multistatic sensing configurations, and a general system model that unifies the signal, channel, and optimization formulations used across the literature.
- 2) **Systematic Review of Six Technical Domains:** We provide a structured review of six interconnected research areas critical for real-world UAV-ISAC deployment, each supported by a dedicated comparative table (Tables 3–8) covering over 80 methodologies:
  - Channel and target estimation alongside beam-tracking and beamforming (Table 3)
  - System throughput maximization under joint sensing and communication constraints (Table 4)
  - Weighted sum rate (WSR) and sensing performance co-optimization (Table 5)
  - Communication latency and age of information minimization (AoI) (Table 6)
  - Energy-aware trajectory design and system operation (Table 7)

- PLS for resilient UAV-ISAC communications (Table 8)

Each domain review concludes with a Summary and Lessons Learned that synthesizes cross-paper design principles and identifies domain-specific open problems, going beyond cataloging individual contributions to extract actionable insights grounded in the real-world constraints of UAV platforms.

- 3) **Cross-Cutting Challenge Synthesis:** Drawing on the domain-level lessons, Section IV consolidates the open research challenges that cut across all six domains—including realistic propagation modeling, physical controllability constraints, algorithm generalization under imperfect CSI, multi-threat security frameworks, energy-AoI-security co-design, and standardization gaps—providing a research roadmap for the next generation of UAV-ISAC systems.

The remainder of this paper is organized as follows. Section II introduces the fundamentals of UAVs and ISAC, describing UAV operational roles, sensing configurations, and the general system model. Section III reviews advancements across the six technical domains listed above, with each subsection concluding with synthesized design lessons and open problems. Section IV consolidates the cross-cutting research challenges and future directions. Section V concludes the paper by contextualizing UAV-based ISAC within the broader trajectory of 6G wireless systems. The survey's taxonomy is illustrated in Fig. 2.

## II. FUNDAMENTALS OF UAV AND ISAC

This section outlines UAVs enhance communication systems by operating as aerial BSs, Relays, and Transceivers. Through these roles, UAVs optimize the network performance. The discussion also introduces different sensing configurations namely monostatic, bistatic, and multistatic, as they play a central role in UAV-based systems. The section concludes by highlighting the practical advantages achieved through the integration of UAVs and ISAC technology.

### A. ROLES OF UAVS IN ENHANCING COMMUNICATION SYSTEMS

UAVs, commonly referred to as drones, are highly versatile aerial platforms that can be operated either autonomously or by remote control [2], [52]. Owing to their quick deployment, high mobility, and relatively low maintenance requirements, they have become useful tools for a wide range of civilian applications [25]. Typical such applications include real-time traffic monitoring, remote sensing, wireless coverage, package delivery, emergency response, precision agriculture, video surveillance and infrastructure inspection [53]. UAVs are normally categorized by size, operational altitude, and endurance [54]. Although UAVs were first developed for military reconnaissance and combat, mainly to minimize risk to human pilots, their capabilities have since been widely adopted for civilian use. Today, they perform numerous tasks such as aerial surveying, public-safety and security

**TABLE 3.** Summary of channel/target estimation and beam-tracking/beamforming techniques in UAV-ISAC systems.

| Ref. Year                         | UAV Details |   |         | # (UEs) | Sen. Geometry/Type                     | Sensing Metric                             | CSI     | Methodology                                                   | Opt. variables                                                  | Objective                                                                                     | Readiness        |
|-----------------------------------|-------------|---|---------|---------|----------------------------------------|--------------------------------------------|---------|---------------------------------------------------------------|-----------------------------------------------------------------|-----------------------------------------------------------------------------------------------|------------------|
|                                   | Role        | # | Band    |         |                                        |                                            |         |                                                               |                                                                 |                                                                                               |                  |
| Channel/Target Estimation Schemes |             |   |         |         |                                        |                                            |         |                                                               |                                                                 |                                                                                               |                  |
| [93] 2023                         | T           | S | 3.5 GHz | M       | UAV direction sensing relative to HRIS | CE MSE                                     | -       | root MUSIC                                                    | UAV-HRIS and HRIS-BS channels                                   | To maximize UAV-HRIS and HRIS-BS CE accuracy.                                                 | Theory           |
| [94] 2023                         | T&S         | S | —       | M       | GPS, IMU                               | CE                                         | -       | UKF-based fusion                                              | BF, trajectory                                                  | To minimize CE error.                                                                         | Theory           |
| [95] 2022                         | T&S         | M | 2.4 GHz | S       | GU tracking                            | Target position estimation                 | Avail.  | Multiple drone measurements, EKF                              | —                                                               | To minimize position and velocity estimation errors.                                          | Simulation       |
| [96] 2023                         | T&S, BS     | S | —       | M       | Target angle sensing                   | —                                          | Avail.  | Time-division beam searching                                  | —                                                               | Study the impact of UAV jittering on sensing performance.                                     | Theory           |
| [97] 2023                         | T&S         | M | —       | S       | Accurate GU tracking                   | Position estimation CRLB                   | Avail.  | EKF for GU tracking, SCA for trajectory optimization          | Trajectory                                                      | To maximize downlink communication rate.                                                      | Simulation       |
| [98] 2023                         | T&S         | M | —       | M       | Target detection                       | Target detection probability               | Avail.  | Signal reuse for detection, SCA for UAV location optimization | UAV position and Tx power                                       | To maximize the minimum target detection probability.                                         | Simulation       |
| [99] 2024                         | T&S         | M | —       | M       | Gather IoT status information          | Radar estimation rate                      | Avail.  | Iterative optimization algorithm                              | UAV task scheduling, trajectory, and Tx power                   | To maximize information rate.                                                                 | Simulation       |
| [100] 2025                        | T&S         | M | 7 GHz   | S       | A2G GUE sensing                        | Radar estimation rate, detection prob.     | Avail   | Stochastic analysis, MoM, Meijer G-functions, SINR analysis   | UAV selection, beam selection from code-book                    | To analyze CP and DP in sensing-assisted aerial network; beam alignment without CSI feedback. | Simulation       |
| Beam-Tracking/Beamforming Schemes |             |   |         |         |                                        |                                            |         |                                                               |                                                                 |                                                                                               |                  |
| [101] 2023                        | Rx          | M | 28 GHz  | M       | UAV tracking                           | Beam association error                     | Avail.  | EKF, VBO                                                      | BF                                                              | To maximize the achievable rate.                                                              | Hardware Testbed |
| [102] 2023                        | T&S         | S | 28 GHz  | S       | AoA / AoD sensing                      | MSE of AoA / AoD estimation                | Avail.  | Phase / amplitude compensation                                | Elevation and azimuth angle from UAV-BS to the terrestrial user | To maximize the system SNR.                                                                   | Theory           |
| [103] 2024                        | T&S         | S | —       | M       | GPS, IMU                               | Position / orientation estimation accuracy | Avail.  | EKF-based data fusion                                         | BF                                                              | To maximize downlink SE.                                                                      | Simulation       |
| [104] 2024                        | Rx          | M | —       | M       | UAV tracking                           | —                                          | Avail.  | EKF, MUSIC                                                    | BF                                                              | To maximize the achievable communication rate.                                                | Simulation       |
| [105] 2025                        | T&S         | S | —       | M       | GUE detection                          | Beam-pattern gain                          | Avail.  | Dual DNN                                                      | BF, UAV position                                                | To minimize the beam-pattern gain error.                                                      | Simulation       |
| [106] 2025                        | Target      | S | —       | M BS    | Aerial detection                       | SCNR                                       | Avail.  | AO, SCA, Dinkelbach methods                                   | BF                                                              | To maximize the SCNR of sensing.                                                              | Simulation       |
| [107] 2025                        | T&S         | S | —       | M       | GUE detection                          | Target position estimation RMSE            | Perfect | SDR, QSDP, AO, SCA, Dinkelbach's methods, MF, ESPRIT          | BF, UAV position                                                | To maximize the received signal power at the estimated location.                              | Simulation       |
| [108] 2025                        | Target      | S | 30 GHz  | S       | Near-field UAV tracking                | AoA / distance estimation RMSE, CRB        | Avail.  | EKF, MUSIC, SSB algorithm                                     | BF (BS Tx,Rx), UAV jittering                                    | To maximize achievable rate and improve near-field beam tracking accuracy.                    | Simulation       |

Readiness: Theory = theory only (no numerical validation); Simulation = numerical results; Prototype = hardware implementation; Field = real-world testing.

monitoring, package delivery services, precision agriculture, and communications [23]. The following paragraphs describe three key communication-oriented roles played by UAVs.

1) UAV AS AERIAL BS

When deployed as aerial BSs, UAVs provide wireless coverage in areas where terrestrial infrastructure is unavailable or impaired. They are particularly valuable in emergency scenarios, large-scale public events, and temporary hotspots where rapid connectivity is needed. Thus, UAV-BS configurations can help achieve low-latency links, improved

reliability, and better power utilization [55]. In addition, UAV-BSs increasingly rely on state-of-the-art technologies such as millimeter-wave (mmWave), free-space optical (FSO) communication, and LiDAR [56], [57], [58]. These techniques extend coverage and enhance throughput in densely populated or disaster-affected regions [56], [57], [58].

2) UAV AS AERIAL RELAY

UAVs can also act as intermediate relay nodes that strengthen communication links between base stations (BSs) and end users. This role becomes essential when direct links are

TABLE 4. Summary of throughput maximization schemes for UAV-ISAC systems.

| Ref. Year                                                           | UAV Details |   |           | # (UEs) | Sen. Geometry/Type                | Sensing Metric                | CSI       | Methodology                     | Opt. variables                              | Objective                                  | Readiness  |
|---------------------------------------------------------------------|-------------|---|-----------|---------|-----------------------------------|-------------------------------|-----------|---------------------------------|---------------------------------------------|--------------------------------------------|------------|
|                                                                     | Role        | # | Band      |         |                                   |                               |           |                                 |                                             |                                            |            |
| Sensing Beam-Pattern Gain-Based Designs                             |             |   |           |         |                                   |                               |           |                                 |                                             |                                            |            |
| [109] 2023                                                          | T&S         | S | –         | M       | Multiple target sensing           | Sensing beam-pattern gain     | Avail.    | AO, SCA                         | Trajectory, BF                              | To maximize weighted SR                    | Simulation |
| [110] 2023                                                          | T&S         | S | –         | M       | Multiple target sensing           | Sensing beam-pattern gain     | Avail.    | Penalty-based opt.              | Sensing time selection, Trajectory, BF      | To maximize minimum-rate                   | Simulation |
| [111] 2022                                                          | T&S         | S | –         | M       | Single target sensing             | Sensing beam-pattern gain     | Avail.    | SDP                             | Sensing time selection, Trajectory, BF      | To maximize rate                           | Simulation |
| [112] 2024                                                          | T&S         | S | –         | M       | GUEs detection                    | Sensing beam-pattern gain     | Avail.    | AO, PSO                         | Info. & sensing BF, MA array position opt.  | To maximize SR                             | Simulation |
| [113] 2025                                                          | T&S         | S | Sub-6 GHz | M       | Multiple target sensing           | Sensing beam-pattern gain     | Avail.    | AO, SCA, SDR, SQP               | Tx, Sensing BF, Sensing trajectory          | To maximize average weighted Sum-rate      | Simulation |
| Sensing Range, Velocity, and Position Estimation CRLB-Based Designs |             |   |           |         |                                   |                               |           |                                 |                                             |                                            |            |
| [114] 2023                                                          | T&S         | S | 28 GHz    | M       | Target (vehicle) detection        | Radar tracking/prediction     | Avail.    | ML estimation/tracking          | BF                                          | To maximize SE                             | Simulation |
| [115] 2023                                                          | T&S         | M | –         | M       | Mobile GUE detection              | Mobility level detection      | Avail.    | Mobility-aware RA               | UAV-UE association                          | To maximize avg. SR                        | Simulation |
| [116] 2024                                                          | T&S         | M | 30 GHz    | -       | Multiple target sensing           | Range and velocity estimation | Avail.    | ISAC waveform design            | -                                           | -                                          | Theory     |
| [117] 2025                                                          | T&S         | M | –         | M       | Multiple mobile UEs sensing       | Range and velocity estimation | Avail.    | AO, EKF                         | BF, trajectory                              | To maximize SR                             | Simulation |
| [118] 2025                                                          | T&S         | S | –         | M       | Target DOA estimation             | Sensing radar estimation rate | Avail.    | AO                              | BF, trajectory, time-allocation             | To maximize radar estimation rate          | Simulation |
| [119] 2023                                                          | R&S         | S | 30 GHz    | M       | GUE detection                     | Position estimation CRLB      | Avail.    | 3D state transition model       | PA at UAV & BS                              | To maximize SR                             | Simulation |
| [76] 2023                                                           | T&S         | S | –         | M       | Target (vehicle) sensing          | Position estimation CRLB      | Avail.    | AO                              | BF, trajectory                              | To maximize avg. system throughput         | Simulation |
| [120] 2025                                                          | R&S         | S | 6 GHz     | M       | Mobile target detection           | Position estimation CRLB      | Avail.    | RL-DDPG                         | BF, trajectory                              | To maximize SR                             | Simulation |
| [121] 2026                                                          | Relay       | S | –         | M       | Single target sensing             | Sensing SNR                   | Avail.    | AO, SDR, SCA                    | Trajectory, BS BF, RIS PSs                  | To maximize average achievable rate (AAR). | Simulation |
| [122] 2025                                                          | T&S         | S | –         | M       | Ground target detection           | Sensing SINR                  | Avail.    | AO (JCBTO), AWM MSE, SCA        | Comm. scheduling, BF (Tx,Rx), trajectory    | To maximize average sum rate (ASR).        | Simulation |
| Sensing SNR and Rate-Based Designs                                  |             |   |           |         |                                   |                               |           |                                 |                                             |                                            |            |
| [123] 2024                                                          | R&S         | S | –         | M       | Multiple vehicle detection        | Sensing SNR                   | Avail.    | DRL with proximal policy opt.   | Trajectory, BF, RIS PSs, info. & sensing BF | To maximize minimum-rate                   | Simulation |
| [124] 2024                                                          | T&S         | M | –         | M       | Target detection                  | Sensing SNR                   | Avail.    | SCA, SDP                        | UAV-UE association, UAV position opt., BF   | To maximize weighted SR                    | Simulation |
| [125] 2024                                                          | T&S         | M | –         | M       | Vehicle detection                 | Sensing SNR                   | Avail.    | AO, FP, MT, Sequential QP       | Trajectory, UAV-UE association, BF          | To maximize SR                             | Simulation |
| [126] 2025                                                          | Rx          | M | –         | -       | UAV detection                     | Sensing SNR                   | Avail.    | MDP model-based DRL             | Trajectory, BF                              | To maximize SR                             | Simulation |
| [127] 2025                                                          | R&S         | S | –         | S       | Target sensing                    | Sensing SNR                   | Avail.    | SCA                             | Trajectory, BF                              | To maximize SR                             | Simulation |
| [128] 2025                                                          | R&S         | S | 2.7 GHz   | M       | Target sensing                    | Sensing SNR                   | Imperfect | AO, SDP                         | Trajectory, A-RIS design, BF                | To maximize minimum SINR                   | Simulation |
| [129] 2025                                                          | T&S         | S | –         | S       | Target sensing                    | Sensing SNR                   | Avail.    | AO, SCA                         | RHS-UAV design, RIS design, BF              | To maximize rate                           | Simulation |
| [130] 2025                                                          | T&S         | S | –         | M       | Multiple targets detection        | Sensing SNR                   | Avail.    | AO, SDP, SCA                    | STAR-RIS design, BF                         | To maximize SR                             | Simulation |
| [131] 2024                                                          | T&S         | M | –         | M       | IoT-nodes sensing                 | Sensing rate                  | Avail.    | AO                              | Trajectory, node scheduling, PA             | To maximize minimum-rate                   | Simulation |
| [132] 2023                                                          | T&S         | S | –         | S       | Mobile GUE detection              | Sensing rate                  | Avail.    | Deriving differential equations | Trajectory                                  | To design trajectory                       | Theory     |
| [133] 2024                                                          | T&S         | S | –         | S       | GUE position sensing              | Sensing rate                  | Avail.    | SCA                             | Trajectory                                  | To maximize rate                           | Simulation |
| [134] 2025                                                          | Relay       | S | –         | M       | Multiple mobile targets detection | Sensing rate                  | Imperfect | Transfer learning with DDPG, AO | UAV-RIS design, Trajectory, BF              | To maximize SR                             | Simulation |

S- Single, M- Multiple, H- Hybrid, R&S- Relay and Sensing, GUE- Ground UE, Comm.- Communications, max.- maximization, min.- minimize.

BF- beamforming, RA- resource allocation, alg.- algorithm, opt.- optimization, Avail.- available, PA- power allocation, alloc.- allocation, SR- sum-rate.

Perf.- performance, info.- information, PSs- phase shifts, T&S- Transmit and Sensing, SE- spectral efficiency, ML- maximum likelihood.

Readiness: Theory = theory only (no numerical validation); Simulation = numerical results; Prototype = hardware implementation; Field = real-world testing.

**TABLE 5.** Summary of WSR and sensing optimization schemes for UAV-ISAC systems.

| Ref. Year                              | UAV Details |   |        | # (UEs) | Sen. Geometry/Type         | Sensing Metric                         | CSI     | Methodology                                                               | Opt. Variables                                        | Objective                                                                       | Readiness  |
|----------------------------------------|-------------|---|--------|---------|----------------------------|----------------------------------------|---------|---------------------------------------------------------------------------|-------------------------------------------------------|---------------------------------------------------------------------------------|------------|
|                                        | Role        | # | Band   |         |                            |                                        |         |                                                                           |                                                       |                                                                                 |            |
| Sensing SE and Rate-Based Designs      |             |   |        |         |                            |                                        |         |                                                                           |                                                       |                                                                                 |            |
| [135] 2023                             | T&S         | M | —      | M       | GUE position sensing       | Sensing SE                             | Avail.  | MASAC                                                                     | User association, trajectory, PA                      | To maximize the minimum weighted comm. and sensing SE                           | Simulation |
| [136] 2023                             | T&S         | S | 3 GHz  | M       | Multiple UEs sensing       | Sensing rate                           | Avail.  | LP, Rounding alg.                                                         | UAV position, subcarrier alloc. for sensing and comm. | To maximize the minimum weighted comm. and sensing rate                         | Simulation |
| [137] 2024                             | T&S         | M |        | S       | A2G target sensing         | Radar estimation rate, detection prob. | Avail.  | Stochastic geometry, analysis, selection<br>SIR UAV                       | BW allocation, UAV selection                          | To analyze and optimize sensing-comm. trade-off under bandwidth constraint.     | Simulation |
| Position Estimation CRLB-Based Designs |             |   |        |         |                            |                                        |         |                                                                           |                                                       |                                                                                 |            |
| [138] 2023                             | T&S         | S | —      | S       | Target sensing             | Target position estimation             | Avail.  | Gradient descent                                                          | Trajectory                                            | To jointly maximize rate and minimize CRLB for target position                  | Simulation |
| [139] 2024                             | T&S         | S | —      | M       | Multiple target sensing    | Position estimation CRLB               | Avail.  | SCA, Gradient descent                                                     | Trajectory, BW alloc.                                 | To jointly maximize rate and minimize CRLB for target position                  | Simulation |
| [140] 2025                             | Tx          | S | 28 GHz | M       | Target DOA estimation      | Position estimation CRLB               | Avail.  | DRL                                                                       | Trajectory, STARS design, BF                          | To jointly maximize UE SINR and minimize CRLB for target localization           | Simulation |
| [141] 2025                             | T&S         | M | —      | M       | Users localization         | Position estimation CRLB               | Avail.  | LLM-enabled evolutionary algorithm                                        | UAV placement, PA                                     | To jointly maximize UEs rate and minimize CRLB for UEs localization             | Simulation |
| [142] 2025                             | T&S         | M | 35 GHz | M       | Multiple target sensing    | Position estimation CRB                | Avail.  | SC-DO-MUOA, EAG-MOEA/D with hybrid PSO-GA, multi-stage constraint control | Trajectory, user/target association, PA               | To maximize comm. sum rate & minimize sensing CRB.                              | Simulation |
| Sensing SNR and Power-Based Designs    |             |   |        |         |                            |                                        |         |                                                                           |                                                       |                                                                                 |            |
| [143] 2025                             | T&S         | M | —      | M       | Target detection           | Sensing SNR                            | Avail.  | AO                                                                        | Trajectory, PA, time scheduling, radar WPT waveform   | To jointly maximize the minimum comm. rate & Sensing SINR                       | Simulation |
| [144] 2024                             | T&S         | M | —      | M       | Target (vehicle) detection | Sensing SNR                            | Avail.  | AO                                                                        | RIS PSs, DFRC BF, trajectory UE scheduling            | To maximize weighted avg. of SR and sensing SNR                                 | Simulation |
| [145] 2025                             | T&S         | S | —      | M       | Target sensing             | Sensing SNR                            | Avail.  | Multi agent DRL, DDPG, TD3, PPO                                           | Trajectory, RIS PSs, BF                               | To maximize throughput and sensing SNR                                          | Simulation |
| [146] 2025                             | T&S         | S | —      | M       | Users localization/sensing | Sensing SNR                            | Avail.  | BCD, SCA                                                                  | Trajectory, ISAC scheduling, PA                       | To maximize weighted communication and sensing SNR                              | Simulation |
| [147] 2024                             | T&S         | M | —      | M       | Multiple target sensing    | Sensing power                          | Avail.  | AO, SCA                                                                   | BF, trajectory, UAV-UE association                    | To maximize weighted SR and radar received power                                | Simulation |
| [148] 2025                             | T&S         | S | —      | M       | Multiple target sensing    | Sensing power                          | Perfect | MCI-ADMM, Lagrangian                                                      | Joint BF and RIS PS                                   | To minimize the weighted sum of MUI for communication and BPM                   | Simulation |
| [149] 2025                             | T           | S | 2 GHz  | M       | BS-to-UAV sensing          | Sensing SNR                            | Avail.  | MoE-PPO (DRL with mixture of experts)                                     | BS BF, RIS PSs                                        | To maximize sensing SNR while ensuring users QoS, Power budget, Discrete phase. | Simulation |

Readiness: Theory = theory only (no numerical validation); Simulation = numerical results; Prototype = hardware implementation; Field = real-world testing.

blocked by terrain or buildings [59]. Their dynamic repositioning capability improves network performance and coverage in real time, especially becoming beneficial in challenging environments like urban landscapes or remote locations [60], [61], [62].

### 3) UAV AS AERIAL TRANSCEIVER

In some deployments, UAVs operate as transceivers, or even as aerial user equipment (UE), that communicate directly with both terrestrial and aerial nodes. They exchange essential information such as altitude and flight mode, improving

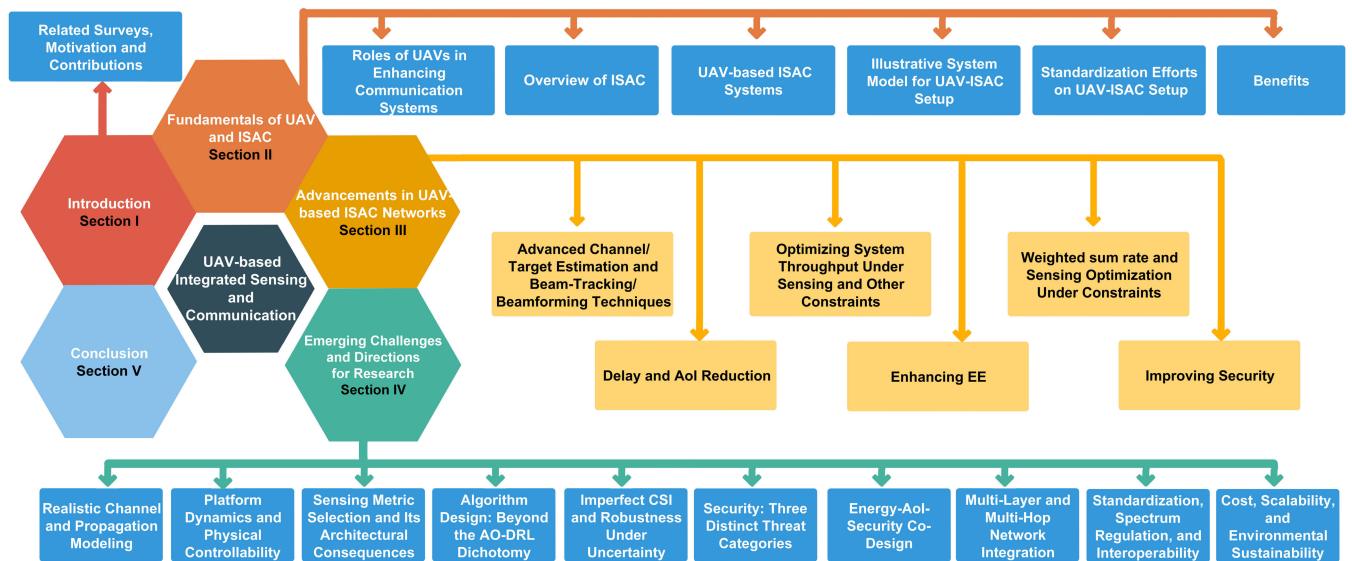
network performance, especially when faced with challenges like latency and throughput [63]. Because UAVs typically maintain LoS connections, they experience interference patterns that differ from those of ground devices. Managing these unique interference conditions requires advanced coordination, control, and security mechanisms [64], [65], [66].

### B. OVERVIEW OF ISAC

The integration of wireless communication technologies (e.g., networks, signal processing) with sensing technologies (e.g., radar, vision, and LiDAR) into a single operational

**TABLE 6.** Summary of delay and AoI strategies for UAV-ISAC systems.

| Ref. Year  | UAV Details |   |          | # (UEs) | Sen. Geometry/Type                | Sensing Metric                                  | CSI    | Methodology         | Opt. Variables                                                            | Objective                                                                      | Readiness  |
|------------|-------------|---|----------|---------|-----------------------------------|-------------------------------------------------|--------|---------------------|---------------------------------------------------------------------------|--------------------------------------------------------------------------------|------------|
|            | Role        | # | Band     |         |                                   |                                                 |        |                     |                                                                           |                                                                                |            |
| [150] 2021 | T&S         | M | —        | NA      | Sensing at ground and air         | Sensing accuracy                                | Avail. | EKF, IFF            | —                                                                         | To improve sensing accuracy and reduce comm. delay for safe flight.            | Simulation |
| [151] 2024 | R&S, FC     | M | 76.5 GHz | M       | Environmental or situational data | Successful sensing prob., delay violation prob. | Avail. | PCP, SNC            | PA                                                                        | To minimize network-layer delay to evaluate tradeoff between sensing and comm. | Simulation |
| [152] 2024 | T&S, BS     | M | 1.4 GHz  | M       | Ground target detection           | Target position estimation                      | Avail. | DPSO, CNN           | Trajectory and user association                                           | To maximize communication throughput.                                          | Simulation |
| [153] 2023 | T&S         | S | —        | M       | Ground target detection           | Target position estimation                      | Avail. | Dynamic programming | Trajectory                                                                | To maximize UAV's communication AoI.                                           | Simulation |
| [154] 2023 | T&S         | S | —        | M       | Data sensing                      | Sensing time                                    | Avail. | SCA                 | Position, Comm. time, Power                                               | To minimize the average Peak Age-of-Information.                               | Simulation |
| [155] 2021 | T&S         | S | —        | M       | Data sensing                      | Sensing time, power                             | Avail. | SCA                 | Comm. time, Power, Trajectory                                             | To minimize the maximum average Peak Age-of-Information of targets.            | Simulation |
| [156] 2025 | T&S         | S | —        | M       | Target sensing                    | Radar estimation rate                           | Avail. | MINLP               | Sensing scheduling, duration, Tx power, operating frequency, & trajectory | To maximize the volume of sensing data while minimizing AoI.                   | Simulation |
| [157] 2025 | T&S         | S | 6–8 GHz  | S       | Data sensing                      | Radar mutual information                        | Avail. | Hybrid PSO-GA       | BW, Power and UAV location                                                | To maximize the fair sum rate under latency and reliability constraints.       | Simulation |



**FIGURE 2.** Taxonomy of the paper.

framework is commonly referred to as ISAC [16], [22]. In essence, ISAC allows communication and sensing to share key resources such as spectrum, hardware, and computational power [15], [36]. This convergence makes it possible for UAVs to collect and transmit multimodal data in a synchronized and efficient manner, thereby improving their overall operational effectiveness. Sensing involves using radio signals to identify and analyze characteristics of objects in the environment such as range, velocity, position, orientation, size, shape, imagery and even material composition [22]. When sensing capabilities are embedded into communication networks, those networks effectively act as distributed radar sensors. They not only exchange information but also observe and interpret their surroundings efficiently and effectively.

In the domain of sensing for communication, the integration of sensing data, such as CSI and user location, plays a critically important role in improving the performance of communication via optimized CE and beamforming [16], [36]. This integration guarantees reliable connectivity in dynamic environments as well as supports applications like beam tracking, interference management, and real-time urban communication [12], [16]. On the contrary, communication for sensing effectively utilizes the communication backend infrastructure, enhancing tasks such as object detection and localization. By exploiting feedback signals and shared data, it can significantly improve sensing accuracy, robustness, and coordination among elements of nodes that are critical for applications in surveillance,

**TABLE 7.** Summary of EE schemes for UAV-ISAC systems.

| Ref. Year                                                               | UAV Details |   |        | # (UEs) | Sen. Geometry/Type                       | Sensing Metric                           | CSI    | Methodology                                 | Opt. Variables                                             | Objective                                                                                   | Readiness  |
|-------------------------------------------------------------------------|-------------|---|--------|---------|------------------------------------------|------------------------------------------|--------|---------------------------------------------|------------------------------------------------------------|---------------------------------------------------------------------------------------------|------------|
|                                                                         | Role        | # | Band   |         |                                          |                                          |        |                                             |                                                            |                                                                                             |            |
| Sensing Distance, SINR, Angle, and Position-Based Designs               |             |   |        |         |                                          |                                          |        |                                             |                                                            |                                                                                             |            |
| [158] 2022                                                              | T&S         | S | –      | S       | Traffic perception environment mapping   | –                                        | Avail. | SCA                                         | Task offloading and resource allocation for data fusion    | To minimize UAV latency and energy consumption.                                             | Simulation |
| [159] 2023                                                              | T&S         | S | –      | S       | Ground target detection                  | Distance between UAV and target          | Avail. | DRL                                         | Trajectory                                                 | To maximize the number of connected devices and minimize the energy consumption of the UAV. | Simulation |
| [160] 2023                                                              | T&S         | S | –      | S       | Ground target detection, surveillance    | Radar SINR                               | Avail. | POS, ST                                     | User scheduling, power, and trajectory                     | To maximize EE and sensing fairness.                                                        | Simulation |
| [161] 2023                                                              | T&S         | S | –      | S       | Ground target detection                  | BF accuracy                              | Avail. | SDR, the big-M method, and SCA              | Trajectory, velocity, and BF                               | To minimize average power consumption, and ensure communication and sensing QoS.            | Simulation |
| [162] 2023                                                              | T&S         | S | –      | S       | Ground target detection                  | Target position estimation               | Avail. | SCA, BCD                                    | Trajectory                                                 | To minimize UAV propulsion power.                                                           | Simulation |
| [163] 2024                                                              | T&S         | S | 28 GHZ | S       | Ground target tracking                   | Target angle estimation accuracy         | Avail. | EKF, BCD based FP algorithm                 | Number of activated antennas, BF                           | To maximize EE.                                                                             | Simulation |
| [164] 2024                                                              | T&S         | S | –      | S       | Ground target detection, area monitoring | Ground target accumulated sensing energy | Avail. | One-step LRA from DP and SDP                | Trajectory, BF, and mission time                           | To maximize accumulated sensing energy and ensure communication QoS.                        | Simulation |
| [165] 2025                                                              | T&S         | S | –      | S       | Ground target detection                  | Target estimation accuracy (CRB)         | Avail. | SQP                                         | UAV trajectory & energy-aware operations                   | To optimize communication and sensing performance energy efficiently.                       | Simulation |
| [166] 2024                                                              | T&S         | S |        | M       | Multiple target detection                | Received echo SNR                        | Avail. | AO, SDR, big-M, SCA                         | Trajectory, velocity, BF, PA, hovering time                | To minimize UAV power consumption.                                                          | Simulation |
| [167] 2026                                                              | Rx          | M |        | M       | Unauthorized UAV target detection        | Sensing SNR                              | Avail. | Meta-DRL (DeepESC, Meta-GRU actor-critic    | GBS BF, UAV trajectories                                   | To maximize expected EE.                                                                    | Simulation |
| Sensing Information Rate, Mutual Information, and Latency-Based Designs |             |   |        |         |                                          |                                          |        |                                             |                                                            |                                                                                             |            |
| [168] 2023                                                              | T&S         | S | –      | S       | Recognize static targets                 | Radar estimation information rate        | Avail. | BCD, ML                                     | Sensing scheduling, number of time-slots, and trajectory   | To minimize UAV energy consumption and data collection time.                                | Simulation |
| [169] 2023                                                              | T&S         | S | –      | S       | Ground target detection                  | Radar mutual information                 | Avail. | SCA, FP                                     | User scheduling, Tx power, and trajectory                  | To maximize EE and min radar MI.                                                            | Simulation |
| [170] 2024                                                              | T&S         | M | –      | M       | Vehicle sensing                          | Sensing mutual information               | Avail. | MARL                                        | Tx power, trajectory                                       | To improve sensing MI obtained by UAVs, improve comm. quality, save UAVs comm. energy.      | Simulation |
| [171] 2025                                                              | T&S         | M | –      | M       | Ground target detection                  | Sensing latency                          | Avail. | DRL-A3C                                     | BW, Power, computing capacity                              | To maximize ISCC service success rate and UAV EE.                                           | Simulation |
| [172] 2025                                                              | T&S         | M | –      | M       | Ground target tracking                   | Sensing latency                          | Avail. | EKF, SDR, SCA                               | BW, Power, computing capacity                              | To maximize UAV EE.                                                                         | Simulation |
| [173] 2026                                                              | R&S         | S | 2 GHz  | M       | Ground target detection (anti-jamming)   | Sensing SINR                             | Avail. | SG-SD3 (Stackelberg game + soft double DPG) | BS Tx power, RIS RCs., active RIS ratio, channel selection | To maximize EE under jamming.                                                               | Simulation |

emergency response, and military operations [16], [19], [67], [68].

1) TYPES OF SENSING

In ISAC systems, three principal sensing methods are used, namely monostatic, bistatic, and multistatic sensing [19], [45]. Each of these methods possesses unique strengths, making them more suitable for various types of applications.

a: MONOSTATIC SENSING

Monostatic sensing comprises a single unit that transmits and receives the signal. This type of sensing is commonly used in radar systems for tasks such as Earth observation and environmental monitoring [45]. Thus, the simplicity of using a single unit for both transmission and reception renders the whole process efficient, especially when the system has limited size or power. It can calculate the key parameters,

such as distance and speed, after analyzing the time delay and Doppler shift of the signal.

b: BISTATIC SENSING

On the other hand, bistatic sensing uses two discrete units: one for transmission and the other for reception. This method allows for more flexible sensing geometries and better coverage by offering multiple angles of observation. Since it reduces interference and improves detection in complex environments, it becomes particularly effective for tracking moving objects or mapping terrain [36].

c: MULTISTATIC SENSING

Multistatic sensing takes the idea of Bistatic Sensing further by using multiple transmitters and receivers at multiple locations. The effect of this configuration is improved spatial coverage, improved detection accuracy, and more

TABLE 8. Summary of secure communication schemes for UAV-ISAC systems.

| Ref. Year                          | UAV Details |          |           | # (UEs) | # (Eves/ Wardens) | Sen. Geometry/type                                     | Sensing Metric                           | Eve's CSI  | Methodology                                 | Opt. Variables                                                              | Objective                                                         | Readiness  |
|------------------------------------|-------------|----------|-----------|---------|-------------------|--------------------------------------------------------|------------------------------------------|------------|---------------------------------------------|-----------------------------------------------------------------------------|-------------------------------------------------------------------|------------|
|                                    | Role        | # (UAVs) | Band      |         |                   |                                                        |                                          |            |                                             |                                                                             |                                                                   |            |
| Single Eve/Warden-Based Designs    |             |          |           |         |                   |                                                        |                                          |            |                                             |                                                                             |                                                                   |            |
| [174] 2023                         | T&S         | S        | —         | S       | S                 | Mobile GUE detection                                   | Delay measurements via sensing echoes    | Avail.     | SCA, EKF                                    | Trajectory                                                                  | To maximize secrecy rate                                          | Simulation |
| [181] 2024                         | T&S         | S        | —         | M       | S                 | Eve detection                                          | Eve's detection SNR                      | Avail.     | BCD, SDP                                    | Jamming/ sensing BF, information BF, trajectory                             | To maximize sum secrecy rate                                      | Simulation |
| [175] 2024                         | T&S and R&S | S        | —         | M       | S                 | Eve detection                                          | -                                        | -          | -                                           | -                                                                           | To maximize sum secrecy rate                                      | Simulation |
| [176] 2024                         | R&S         | S        | —         | M       | S                 | Eve detection                                          | Sensing SNR                              | Avail.     | SCA                                         | UAV position, BF, AN power, RIS PSs                                         | To maximize sum secrecy rate                                      | Simulation |
| [177] 2024                         | T&S         | S        | —         | M       | S                 | Target detection                                       | Target's received power                  | Not avail. | TDMA, SCA, AO, MO                           | Users & targets scheduling, trajectory, PA, RIS PSs                         | To maximize average secrecy rate                                  | Simulation |
| [178] 2025                         | T&S         | S        | —         | M       | S                 | Eve detection                                          | Target's received power                  | Avail.     | PSO, SDR, MM, ADMM                          | UAV position, Tx BF, and RIS BF                                             | To minimize CRB while satisfying users' QoS and secrecy rate      | Simulation |
| [186] 2025                         | T&S         | M        | —         | M       | S                 | Eve and target sensing                                 | Target's sensing rate                    | Avail.     | AO, SCA                                     | Trajectory, BF                                                              | To maximize sum communication rate                                | Simulation |
| [179] 2025                         | T&S         | S        | —         | S       | S                 | Ground target detection                                | Sensing beam pattern gain                | Avail.     | AO, SCA, SDP                                | Trajectory, BF                                                              | To maximize secrecy rate                                          | Simulation |
| [180] 2025                         | R&S         | M        | —         | M       | S                 | UAVs' detection                                        | Sensing SNR                              | Imperfect  | AO, SCA                                     | Trajectory, UAV-RIS design, BF                                              | To maximize sum secrecy rate                                      | Simulation |
| [182] 2025                         | T&S         | S        | —         | M       | Single Warden     | Target detection                                       | Target's received power                  | Avail.     | AO, SCA                                     | PA, trajectory, communication scheduling                                    | To maximize minimum communication rate s.t. covertness constraint | Simulation |
| [183] 2025                         | Eves        | S        | Sub-6 GHz | M       | S                 | UAV (Eve) detection                                    | Target detection prob.                   | Avail.     | AO, SDR, Gaussian randomization, Dinkelbach | Sensing BF, comm. BF, IRS reflection matrix, jammer activation.             | To maximize covert transmission rate.                             | Simulation |
| [184] 2026                         | T&S         | M        | Sub-6 GHz | M       | S                 | Multiple ground target detection (monostatic-bistatic) | Sensing SINR                             | Avail.     | BCD, SDR, SCA, greedy algorithm             | Dual-UAV trajectory, source BF, jamming BF                                  | To maximize average secrecy rate (ASR).                           | Simulation |
| [185] 2026                         | T&S         | S        | Sub-6 GHz | M       | S                 | Target sensing + warden detection                      | Sensing SINR                             | Imperfect  | MM, SCA, Bernstein-type inequality, AO      | DL transmit signal, UL receive BF, RHS weights, users' UL power, trajectory | To maximize minimum covert transmission rate (CTR).               | Simulation |
| Multiple Eves/Warden-Based Designs |             |          |           |         |                   |                                                        |                                          |            |                                             |                                                                             |                                                                   |            |
| [187] 2024                         | T&S         | M        | —         | M       | M                 | Eve detection                                          | Eves' sensing SNR                        | Avail.     | SCA                                         | User scheduling, trajectory, PA                                             | To maximize sum secrecy rate                                      | Simulation |
| [188] 2025                         | T&S         | M        | —         | S       | Multiple UAVs     | UAVs' detection                                        | Target UAVs' position and motion sensing | Avail.     | EKF, SCA, SDP                               | Trajectory, BF                                                              | To maximize communication rate                                    | Simulation |
| [189] 2025                         | Eves        | M        | —         | M       | Multiple UAVs     | UAVs detection                                         | Targets' (UAVs') sensing SNR             | Avail.     | LSTM-based deep NN, SCA, ZF                 | BF                                                                          | To maximize sum secrecy rate                                      | Simulation |
| [190] 2025                         | T&S         | S        | 2 GHz     | S       | Multiple Wardens  | Multiple detection                                     | Sensing BF gain                          | Avail.     | BCD                                         | Trajectory, BF                                                              | To maximize communication rate s.t. covertness constraint         | Simulation |
| [191] 2025                         | T&S         | M        | Sub-6 GHz | M       | M                 | Eavesdroppers detection                                | Sensing SINR                             | Imperfect  | MADRL (robust PPO), FP, SCA                 | UAV trajectory, RIS PSs, BF, user association                               | To maximize secrecy rate.                                         | Simulation |

comprehensive monitoring from different perspectives. Multistatic sensing is considered best solution for large-scale applications like surveillance or environmental monitoring, where tracking multiple targets or ensuring high reliability is of utmost importance [16], [19].

### C. UAV-BASED ISAC SYSTEMS

UAVs are particularly well-suited for ISAC systems owing to their mobility and ease of deployment. These systems

effectively combine both sensing and communication functions within a shared spectrum, hardware, and processing framework, enhancing operational efficiency. In UAV applications, ISAC enables real-time data transmission while ensuring environmental awareness at the same time. This functionality supports a wide range of critical tasks such as surveillance, disaster response, and navigation.

Historically, wireless communication and radar sensing used to operate on separate spectrum bands. But recently,

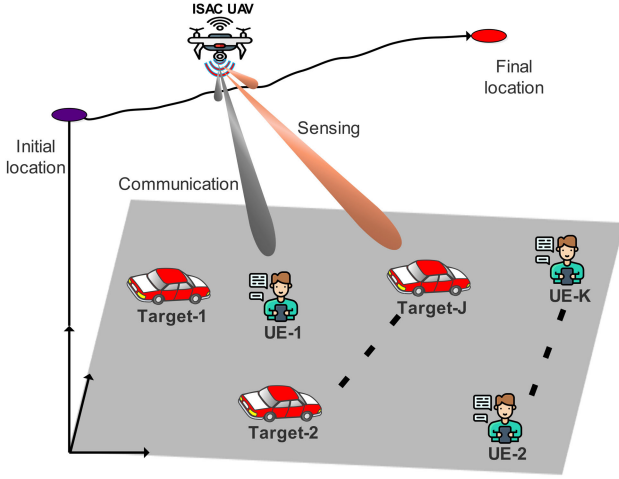


FIGURE 3. Illustrative system model of UAV-based ISAC system.

the shift toward higher-frequency cellular networks (e.g., sub-6 GHz, mmWave, THz) and the demand for multifunctional systems have substantially increased interest in ISAC [19], [69]. By consolidating spectrum and RF infrastructure, ISAC addresses spectrum scarcity and reduces size, weight, and power (SWaP) requirements, which are considered critical for UAV integration into B5G/6G networks.

ISAC implementations range from separate radar and communication waveforms with interference management [70] to dual-function radar-communication (DFRC) systems [71]. These DFRC Systems support simultaneous S&C for functions like SAA and adversary detection. The DFRC designs include:

- **Radar-centric:** Radar-oriented waveforms embed communication data, offering robust sensing performance yet at limited data rates [72].
- **Communication-centric:** While communication waveforms (e.g., OFDM) serve sensing as a secondary function [72], [73], high mobility may cause Doppler-related degradation [74].
- **Integrated designs:** Jointly optimize sensing and communication, e.g., hybrid radar-communication waveforms with optimized covariance matrices that preserve radar beam patterns yet to make sure that the minimum SINR for communication users is maintained [75].

#### D. ILLUSTRATIVE SYSTEM MODEL FOR UAV-ISAC SETUP

To provide a general system model setup, an illustration of UAV-based ISAC system is shown in Fig. 3. A UAV is equipped with a uniform linear array (ULA) comprising  $N_t$  transmit antennas and  $N_r$  receive antennas for communication and sensing, respectively. It flies from a preset initial location to the final location to serve  $K$  single-antenna user equipments (UEs), while simultaneously sensing  $J$  targets on demand. The total flight time is  $T$  seconds, which is divided into  $I$  time slots, each with a duration of  $\tau = T/I$ , for

convenience. Thus, the transmit signal of the UAV at time slot  $i \in \{1, \dots, I\}$  is given by

$$\mathbf{x}_i = \sum_{k=1}^K \mathbf{w}_{k,i} s_{k,i} + \sum_{j=1}^J \mathbf{v}_{j,i} \bar{s}_{j,i}, \quad (1)$$

where  $\mathbf{w}_{k,i} \in \mathbb{C}^{N_t \times 1}$  and  $\mathbf{v}_{j,i} \in \mathbb{C}^{N_t \times 1}$  are the transmit beam-forming vectors for communication and sensing, respectively.  $s_{k,i} \sim \mathcal{CN}(0, 1)$  and  $\bar{s}_{j,i}$  are the uncorrelated communication signal and dedicated sensing signal, respectively. The elements of  $\bar{s}_{j,i}$ ,  $\forall j$  are independent and each of which has zero mean and unit variance.

##### 1) COMMUNICATION MODEL OF UAV-ISAC SETUP

Let  $\mathbf{h}_{k,i}$  denote the wireless channel between the UAV and UE  $k$  at time slot  $i$ , which is given by

$$\mathbf{h}_{k,i} = \sqrt{\frac{\kappa \gamma_{k,i}^{\text{LoS}}}{\kappa + 1}} \mathbf{h}_{k,i}^{\text{LoS}} + \sqrt{\frac{\gamma_{k,i}^{\text{NLoS}}}{\kappa + 1}} \mathbf{h}_{k,i}^{\text{NLoS}}, \quad (2)$$

where  $\gamma_{k,i}^{\text{LoS}} = \beta_0 d_{k,i}^{-2}$  and  $\gamma_{k,i}^{\text{NLoS}} = \beta_0 d_{k,i}^{-\alpha}$  denote the path losses of the line-of-sight (LoS) and non-line-of-sight (NLoS) channels between the UAV and UE  $k$  at time slot  $i$ , respectively,  $\kappa$  is the Rician  $K$ -factor,  $\mathbf{h}_{k,i}^{\text{LoS}}$  and  $\mathbf{h}_{k,i}^{\text{NLoS}}$  represent the small-scale fading components of the LoS and NLoS channels between the UAV and UE  $k$  at time slot  $i$ , respectively,  $\beta_0$  denotes the channel power gain at a reference distance of 1 m,  $\alpha$  is the path-loss exponent for the NLoS link,  $d_{k,i} = \sqrt{z_i^2 + |\mathbf{q}_i - \mathbf{q}_{k,i}|^2}$  is the distance between the UAV and UE  $k$ , where  $z_i$  is the UAV altitude at time slot  $i$ ,  $\mathbf{q}_i = (x_i, y_i)$  denotes the UAV horizontal coordinates, and  $\mathbf{q}_{k,i} = (x_{k,i}, y_{k,i})$  denotes the coordinates of UE  $k$ .

In particular, the LoS channel  $\mathbf{h}_{k,i}^{\text{LoS}}$  in (2) is determined by the transmit steering vector  $\mathbf{h}_{k,i}^{\text{LoS}} \triangleq \left[ 1, e^{-j \frac{2\pi d}{\lambda} \sin \theta_{k,i}}, \dots, e^{-j \frac{2\pi (N_t-1)d}{\lambda} \sin \theta_{k,i}} \right]^T$  where  $d$  is the antenna separation,  $\lambda$  is the carrier wavelength, and  $\theta_{k,i}$  is the angle-of-departure (AoD) or elevation angle. The NLoS channel  $\mathbf{h}_{k,i}^{\text{NLoS}} \sim \mathcal{CN}(\mathbf{0}_{N_t}, \mathbf{I}_{N_t})$  follows a complex Gaussian distribution with zero mean and unit covariance matrix.

The signal received by the UE  $k$  can be expressed as:

$$y_{k,i} = \underbrace{\mathbf{h}_{k,i}^H \mathbf{w}_{k,i} s_{k,i}}_{\text{Intended signal}} + \underbrace{\sum_{\bar{k} \neq k} \mathbf{h}_{k,i}^H \mathbf{w}_{\bar{k},i} \bar{s}_{\bar{k},i}}_{\text{Inter-user interference}} + \underbrace{\sum_{j=1}^J \mathbf{h}_{k,i}^H \mathbf{v}_{j,i} \bar{s}_{j,i}}_{\text{Sensing interference}} + \underbrace{n_{k,i}}_{\text{AWGN}}, \quad (3)$$

where  $n_{k,i} \sim \mathcal{CN}(0, \sigma_k^2)$  is the additive white Gaussian noise (AWGN) at UE  $k$  during time slot  $i$ . Using (3), the signal-to-interference-plus-noise-ratio (SINR) at the UE  $k$  is given by

$$\gamma_{k,i} = \frac{|\mathbf{h}_{k,i}^H \mathbf{w}_{k,i}|^2}{\sum_{\bar{k} \neq k} |\mathbf{h}_{k,i}^H \mathbf{w}_{\bar{k},i}|^2 + \sum_{j=1}^J |\mathbf{h}_{k,i}^H \mathbf{v}_{j,i}|^2 + \sigma_k^2}, \quad (4)$$

Then, the throughput for UE  $k$  at time slot  $i$  is given by

$$r_{k,i} = \log_2(1 + \gamma_{k,i}), \quad (5)$$

## 2) SENSING MODEL OF UAV-ISAC SETUP

The signals transmitted by the UAV are reflected from the targets and then received by the UAV. The sensing channel of the target  $j$  at time slot  $i$ ,  $\mathbf{G}_{j,i} \in \mathbb{C}^{N_r \times N_t}$  can be modeled as [76]

$$\mathbf{G}_{j,i} = \kappa_{j,i} \left( \sqrt{\frac{\bar{\kappa}_{j,i}^{\text{LoS}}(\bar{d}_{j,n})}{\bar{\kappa} + 1}} \mathbf{G}_{j,i}^{\text{LoS}} + \sqrt{\frac{\bar{\kappa}_{j,i}^{\text{NLoS}}(\bar{d}_{j,n})}{\bar{\kappa} + 1}} \mathbf{G}_{j,i}^{\text{NLoS}} \right). \quad (6)$$

where  $\kappa_{j,i} \sim \mathcal{CN}(0, \bar{\sigma}_j^2)$  is the complex reflection coefficient,  $\sigma_j$  represents the complex radar cross-section (RCS) [77],  $\bar{\kappa}_{j,i}^{\text{LoS}}(\bar{d}_{j,n})$  and  $\bar{\kappa}_{j,i}^{\text{NLoS}}(\bar{d}_{j,n})$  denote the round-trip path losses of the LoS and NLoS channels between UAV and the target  $j$  at time slot  $i$ , respectively,  $\bar{\kappa}$  is the Rician  $K$ -factor,  $\mathbf{G}_{j,i}^{\text{LoS}}$  and  $\mathbf{G}_{j,i}^{\text{NLoS}}$  represent the small-scale fading components of the round-trip LoS and NLoS channels between the UAV and the target  $j$  at time slot  $i$ , respectively, and  $\bar{d}_{j,i} = \sqrt{H^2 + |\mathbf{q}_i - \bar{\mathbf{q}}_{j,i}|^2}$  is the distance between the UAV and target  $j$ , where  $\bar{\mathbf{q}}_{j,i} = (\bar{x}_{j,i}, \bar{y}_{j,i})$  denotes the coordinates of the target  $j$ .

The round-trip LoS channel  $\mathbf{G}_{j,i}^{\text{LoS}}$  in (6) is given by  $\mathbf{G}_{j,i}^{\text{LoS}} = \mathbf{a}_{r,j,i} \mathbf{a}_{t,j,i}^H$ , with  $\mathbf{a}_{w,j,i} = [1, e^{-j\frac{2\pi d}{\lambda} \sin \bar{\theta}_{j,i}}, \dots, e^{-j\frac{2\pi(N_w-1)d}{\lambda} \sin \bar{\theta}_{j,i}}]^T$ ,  $w \in \{t, r\}$  denoting the “transmit” or “receive” steering vectors of ULAs at the UAV, and  $\bar{\theta}_{j,i}$  being the elevation angle of the target  $j$  relative to the UAV. The round-trip NLoS channel  $\mathbf{G}_{j,i}^{\text{NLoS}} \in \mathbb{C}^{N_r \times N_t}$  has entries that are complex Gaussian random variables with zero mean and unit variance.

The reflected echo signals at the UAV can be expressed as:

$$\begin{aligned} \bar{\mathbf{y}}_i = & \underbrace{\sum_{j=1}^J \mathbf{G}_{j,i} \mathbf{x}_i}_{\text{Intended signal from } J \text{ targets}} + \underbrace{\sum_{\ell=1}^L \bar{\mathbf{G}}_{\ell,i} \mathbf{x}_i}_{\text{Clutter}} \\ & + \underbrace{\bar{\mathbf{G}}_{\text{SL},i} \mathbf{x}_i}_{\text{Residual self-interference}} + \underbrace{\bar{\mathbf{n}}_i}_{\text{AWGN at UAV}}, \end{aligned} \quad (7)$$

where  $\bar{\mathbf{G}}_{\ell,i} \in \mathbb{C}^{N_r \times N_t}$  is the round-trip channel between UAV and the clutter  $\ell \in 1, \dots, L$ ,  $\bar{\mathbf{G}}_{\text{SL},i} \in \mathbb{C}^{N_r \times N_t}$  is the residual self-interference (SI) channel between the transmit and receive ULAs at UAV, and  $\bar{\mathbf{n}}_i \sim \mathcal{CN}(0, \bar{\sigma}^2)$  is the AWGN at the UAV during time slot  $i$ . By applying the receive beamforming  $\mathbf{u}_i$  at the UAV to sense the target  $j$ , the signal-to-clutter-plus-noise-ratio (SCNR), or sometimes referred to as “sensing SNR”, at the UAV is given by

$$\bar{\gamma}_{j,i} = \frac{|\mathbf{u}_i^H \mathbf{G}_{j,i} \mathbf{x}_i|^2}{\sum_{\bar{j} \neq j} |\mathbf{u}_i^H \mathbf{G}_{\bar{j},i} \mathbf{x}_i|^2 + \sum_{\ell=1}^L |\mathbf{u}_i^H \bar{\mathbf{G}}_{\ell,i} \mathbf{x}_i|^2 + |\mathbf{u}_i^H \bar{\mathbf{G}}_{\text{SL},i} \mathbf{x}_i|^2 + \bar{\sigma}^2}, \quad (8)$$

where the first factor in the denominator counts for interference due to multi-target sensing, the second factor denotes the clutter interference, and the third factor represents the residual SI. Using (8), the sensing rate for the target  $j$  at time slot  $i$  is given by

$$\bar{r}_{j,i} = \log_2(1 + \bar{\gamma}_{j,i}), \quad (9)$$

To enhance sensing performance, it is commonly assumed that the self-interference arising from simultaneous transmission and reception is significantly suppressed through appropriate self-interference cancellation techniques. Furthermore, with prior knowledge of the environment, including clutter effects caused by stationary objects and line-of-sight (LoS) propagation, the impact of clutter interference can be neglected. Under these assumptions, the reflected echo in (7) at the UAV can be approximated as

$$\bar{\mathbf{y}}_i \approx \sum_{j=1}^J \mathbf{G}_{j,i} \mathbf{x}_i + \bar{\mathbf{n}}_i \quad (10)$$

Let  $\mathbf{X}_i = [\mathbf{x}_i(1), \dots, \mathbf{x}_i(M)]$  denote the transmitted signal over  $M$  symbols. Similarly, we can stack the received signal  $\bar{\mathbf{Y}}_i = [\bar{\mathbf{y}}_i(1), \dots, \bar{\mathbf{y}}_i(M)]$  and noise  $\bar{\mathbf{N}} = [\bar{\mathbf{n}}_i(1), \dots, \bar{\mathbf{n}}_i(M)]$  for  $M$  symbols. To facilitate the CRB for joint estimation of parameters of interest, e.g., angle of arrivals (AoAs)  $\bar{\boldsymbol{\theta}}_i \triangleq [\bar{\theta}_{1,i}, \dots, \bar{\theta}_{J,i}]^T$ , we can express  $\bar{\mathbf{Y}}_i$  as

$$\bar{\mathbf{Y}}_i = \mathbf{G}_i \mathbf{X}_i + \bar{\mathbf{N}}_i, \quad (11)$$

where  $\mathbf{G}_i = \sum_{j=1}^J \mathbf{G}_{j,i}$ . The Fisher information matrix (FIM) of  $\bar{\boldsymbol{\theta}}_i$ ,  $\mathbf{F}\bar{\boldsymbol{\theta}}_i \in \mathbb{R}^{J \times J}$ , is given by [78]

$$\mathbf{F}\bar{\boldsymbol{\theta}}_i(j, \bar{j}) = \frac{2}{\bar{\sigma}^2} \mathbb{R} \left( \frac{\partial \text{vec}(\mathbf{G}_i \mathbf{X}_i)^H}{\partial \bar{\theta}_{j,i}} \frac{\partial \text{vec}(\mathbf{G}_i \mathbf{X}_i)}{\partial \bar{\theta}_{\bar{j},i}} \right), \quad (12)$$

while CRB is given by the inverse of FIM, i.e., of  $\text{CRB}_{\bar{\boldsymbol{\theta}}_i} = \mathbf{F}\bar{\boldsymbol{\theta}}_i^{-1}$ .

## 3) FREQUENTLY CONSIDERED OBJECTIVE FUNCTIONS, OPTIMIZATION VARIABLES, AND CONSTRAINTS IN UAV-ISAC SETUP

In this subsection, we elaborate on the most frequent objective functions, optimization variables, and constraints considered in the UAV-ISAC setup. Without loss of generality, we assume that the symbol  $\mathbf{o}$  defines the set of optimization variables. To begin with, we first list different types of objective functions that form part of the UAV-ISAC problem formulation:

- The most commonly considered objective is the sum communication rate maximization, i.e.  $\max_{\mathbf{o}} \sum_{k=1}^K r_{k,i}$ , subject to certain constraints on the sensing rate or the CRB of the estimation parameters. Conversely, some problems adopt a dual approach where the sensing rate, or sometimes referred to as *radar mutual information* (MI), is maximized, i.e.,  $\max_{\mathbf{o}} \sum_{j=1}^J \bar{r}_{j,i}$ , subject to quality-of-service constraints on the communication rate.

- A fairness-based objective function is also considered in some problems, which aims to maximize the worst-case performance, i.e.,  $\max_{\mathbf{0}} \min_k r_{k,i}$ .
- Another important metric in ISAC setups is the weighted sum of communication and sensing rate maximization, i.e.,  $\max_{\mathbf{0}} w_c \sum_{k=1}^K r_{k,i} + w_s \sum_{j=1}^J \bar{r}_{j,i}$ , where  $w_c$  and  $w_s$  denote the communication and sensing weights, respectively.
- Some problems incorporate both communication and sensing metrics in the constraints while focusing on total transmit power minimization, i.e.,  $\min_{\mathbf{0}} P(\mathbf{w}, \mathbf{v}) \triangleq \sum_{k=1}^K \|\mathbf{w}_{k,i}\|^2 + \sum_{j=1}^J \|\mathbf{v}_{j,i}\|^2$ .
- Another objective function considered is the EE maximization of the UAV-ISAC setup, i.e.,  $\max_{\mathbf{0}} \frac{\sum_{k=1}^K r_{k,i}}{P(\mathbf{w}, \mathbf{v}) + P_{\text{aero}}}$ , subject to certain constraints on the sensing rate or the CRB of the estimation parameters, where  $P_{\text{aero}}$  refers to the aerodynamic energy consumption of the UAV [76].
- Some papers focus on maximizing the *transmit beam-pattern gain* from the UAV toward the direction of target  $j$ , i.e.,  $\max_{\mathbf{0}} \|\mathbf{G}_{j,i} \mathbf{x}_i\|^2$ .
- A group of papers focuses on minimizing the CRB of the estimation parameters, i.e.,  $\min_{\mathbf{0}} \text{Tr}(\text{CRB}_{\hat{\theta}_i})$ .

The most commonly considered optimization variables are the UAV trajectory  $\mathbf{q}_i$ , the transmit beamforming vectors for communication  $\mathbf{w}_{k,i}, \forall k, i$ , and the sensing beamforming vectors  $\mathbf{v}_{j,i}, \forall j, i$ . In the following, we list different types of constraints that form part of the UAV-ISAC problem formulation:

- One common constraint is on the UAV trajectory, which limits the maximum horizontal and vertical flying speeds, i.e.,  $\frac{\|\mathbf{q}_{i+1} - \mathbf{q}_i\|}{\tau} \leq v_{\text{max}}^{xy}, \forall i$  and  $\frac{|z_{i+1} - z_i|}{\tau} \leq v_{\text{max}}^z, \forall i$ . In addition, constraints are imposed on the maximum and minimum flying altitudes, i.e.,  $z_{\min} \leq z_i \leq z_{\max}$ .
- To ensure QoS for all users and sensing targets, constraints are imposed on the SINR of each user  $k$  and the SCNR of each target  $j$ , i.e.,  $\gamma_{k,i} \geq \gamma_{\text{th}}, \forall k, i$  and  $\bar{\gamma}_{j,i} \geq \bar{\gamma}_{\text{th}}, \forall j, i$ .
- If the objective is not transmit power minimization, a constraint on the total transmit power budget is typically included, i.e.,  $\sum_{k=1}^K \|\mathbf{w}_{k,i}\|^2 + \sum_{j=1}^J \|\mathbf{v}_{j,i}\|^2 \leq P_{\text{max}}$ .
- If not included in the objective, a sensing constraint may be imposed on the sensing rate, i.e.,  $\bar{r}_{j,i} \geq \bar{r}_{\text{th}}, \forall j, i$ , or on the CRB of the estimation parameters, e.g.,  $\text{Tr}(\text{CRB}_{\hat{\theta}_i}) \leq \text{CRB}_{\text{th}}$ .
- Similarly, if not considered in the objective, a constraint can be imposed on the communication rate of each user, i.e.,  $r_{k,i} \geq r_{\text{th}}, \forall k, i$ .

## E. STANDARDIZATION EFFORTS ON UAV-ISAC SETUP

Integrated Sensing and Communication (ISAC) is increasingly viewed as a key enabler for 5G-Advanced (5G-A) and upcoming 6G systems. This has prompted growing standardization efforts across organizations such as 3GPP, ETSI, IEEE, and ITU. Within 3GPP, the groundwork for ISAC can be traced back to Release-16 and Release-17, where positioning capabilities were enhanced through

techniques such as Time Difference of Arrival (TDoA) and Angle of Arrival/Departure (AoA/AoD) for sub-meter localization accuracy [79]. The formal ISAC standardization process gained momentum in Release-18 and Release-19, where ISAC became a major 5G-A research topic involving study items on sensing services, channel modeling, security, architecture, and application enablement [80]. More recent 3GPP efforts particularly emphasize unified sensing-aware channel models, object detection and tracking, and sensing service key performance indicators (KPIs) for future 6G deployments [81].

The European Telecommunications Standards Institute (ETSI) established the Industry Specification Group (ISG)-ISAC in 2023 to develop technical foundations standards for 6G ISAC systems beyond the current scope of 3GPP releases [82]. The group's work covers a broad range of topics, including deployment scenarios, radio channel characterization, sensing evaluation methodologies, evolution of radio access network (RAN) architectures, and privacy and security considerations. In addition, ETSI has identified advanced use cases such as environmental reconstruction, motion recognition, and sensing for intelligent transportation systems. In parallel, IEEE efforts have largely focused on WLAN-based and application-oriented ISAC standardization. Their notable initiatives in that regard include IEEE 802.11bf for Wi-Fi sensing, along with ongoing work on ISAC terminology, performance metrics, and in-cabin vehicular sensing networks [83], [84]. These developments extend ISAC functionality into license-free spectrum and indoor environments, while still supporting interoperability and implementation consistency.

At the international level, the International Telecommunication Union (ITU) has identified ISAC as a key enabler for IMT-2030 and future 6G ecosystems [85]. Within ITU-R, recent reports and recommendations recognize ISAC as a distinct 6G usage scenario, highlighting its ability to combine communication and environmental awareness within a unified infrastructure. In parallel, ITU-T study groups are working on technical reports that address ISAC frameworks, signaling mechanisms, quality-of-service (QoS) support, and emerging concepts such as optical ISAC networking. These efforts are intended to lay the groundwork for globally harmonized frameworks that support ubiquitous sensing, intelligent network operation, and interoperability across multiple domains in future wireless systems [86].

Although UAV-enabled ISAC is not yet considered a dedicated standardization track, recent discussions have increasingly incorporated UAV-assisted sensing and drone detection use cases [86]. For instance, ETSI has begun to consider airborne sensing scenarios, particularly for applications such as environmental reconstruction. Similarly, 3GPP Release-19 studies highlight UAV detection and tracking as important ISAC use cases, especially in the context of critical infrastructure protection and airspace monitoring. Moreover, recent research aligned with 3GPP Rel-19 evaluation assumptions has examined multi-TRP assisted UAV

sensing within cellular ISAC networks. These developments suggest that UAV-ISAC is gradually evolving from a purely research topic toward a candidate for future standardization in 6G systems [87].

### F. BENEFITS

There are many key advantages of integrating S&C in UAV-based ISAC systems. ISAC-enabled UAVs can execute both tasks in a unified manner simply by sharing resources like power and bandwidth, thus optimizing resource utilization, leading to enhanced operational cost and efficiency [88]. As an example, using a common frequency band for both S&C minimizes energy consumption. Additionally, these systems support real-time data sharing, letting UAVs swiftly transmit sensor data to other UAVs or ground stations. This capability is crucially important for time-sensitive missions. Real-time communication and processing can be modeled with delay-tolerant communication systems to refine data transmission for both delay and reliability [89]. ISAC also improves reliability by employing adaptive communication protocols. Additionally, ISAC supports autonomous operations, allowing UAVs to modify their sensing strategies or flight trajectories based on communication feedback they receive, thus greatly enhancing mission efficiency [90], [91].

To assess the extent of benefits of UAV-based ISAC systems, let us take an example scenario of a communication-centric ISAC system, assuming that the transmitted signal performs both communication and sensing functions. The proposed scenario consists of a UAV equipped with a uniform linear array (ULA) and communication with two non-orthogonal multiple access (NOMA) ground user equipment (GUE) using downlink NOMA principles. The UAV-based NOMA superimposed signal also simultaneously senses a passive target employing a monostatic radar configuration. Our aim here is to design a transmit beamformer that ensures a high communication sum rate of NOMA GUE while simultaneously enabling precise target sensing through a receive combiner that minimizes the radar mean squared error (MSE). This formulation highlights the emerging emphasis on designs based on a unified system in future UAV networks, where maximizing spectral efficiency and enhancing environmental perception capabilities must be done simultaneously.

The joint problem is formulated to maximize the communication sum rate of NOMA GUEs and simultaneously minimize the MSE of the received radar echo signal, while bound by the constraints on the transmit and receive beamforming vectors. To tackle the joint optimization problem, we adopt a two-step alternating optimization approach. In the first step, the sensing receive vector is held fixed while the communication transmit beamformer is updated using a regularized minimum MSE criterion. In the second step, with the beamformer fixed, the sensing combiner is derived in closed form through a Wiener-filter formulation that minimizes the radar MSE. In our simulations, the optimization is performed iteratively, with each variable updated in turn until convergence is reached. This procedure yields improved

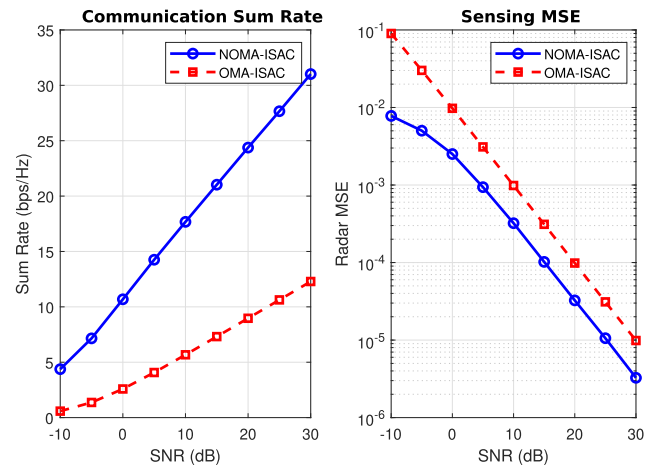


FIGURE 4. UAV-based ISAC-NOMA versus ISAC-OMA system.

performance while keeping the computational cost within a reasonable range.

We conducted MATLAB simulations to evaluate the performance of a UAV-based ISAC system employing power-domain NOMA, and compared it against a conventional OMA UAV-based ISAC architecture. Unless otherwise stated, the system is configured as follows. The UAV is equipped with a ULA comprising 32 antennas, with 16 dedicated to downlink transmission and 16 reserved for echo signal reception, forming a monostatic sensing configuration. The UAV to GUEs communication channels are modeled using Rician fading with unit variance, capturing the line-of-sight characteristics typical in aerial links. The radar echo channel is modeled using Rician fading, reflecting the strong line-of-sight component typically present in UAV-based monostatic sensing. The noise power is set to unity, and the total transmit power is limited to 1 watt. A known pilot symbol is embedded in the transmitted signal to facilitate target detection at the receiver. In the OMA baseline, users are served in orthogonal time or frequency slots, eliminating inter-user interference but at the cost of reduced spectral efficiency. As shown in Fig. 4, the proposed UAV-based ISAC system using NOMA achieves a higher communication sum rate and improved radar sensing performance compared to the OMA counterpart, highlighting the potential of NOMA to improve spectral and hardware efficiency in aerial ISAC systems.

### III. ADVANCEMENTS IN UAV-BASED ISAC NETWORKS

This section reviews recent developments in UAV-enabled ISAC systems, focusing on techniques that improve communication reliability, sensing accuracy, system throughput, EE, latency, and security. The discussion is organized into six main areas: advanced channel estimation and beam tracking, throughput optimization under sensing constraints, joint WSR and sensing optimization, delay and AoI reduction, EE enhancement, and security improvement. Each area is further structured according to sensing metrics and

subdivided by methodology, application scenario, and system configuration. This organization highlights approaches explored for next-generation UAV-ISAC networks, encompassing optimization-based schemes, AI/ML-driven designs, and RIS/STAR-RIS-enabled solutions aimed at tackling their diverse and complex challenges.

#### A. ADVANCED CHANNEL/TARGET ESTIMATION AND BEAM-TRACKING/BEAMFORMING TECHNIQUES

Reliable CE and precise beam management are jointly foundational to UAV-ISAC operation: accurate CE informs the beamformer, while stable beam alignment sustains the channel quality needed for sensing. This subsection is therefore organized into two tightly coupled subcategories. The first, *Channel/Target Estimation Schemes*, examines how UAV-specific impairments—jitter, 3D mobility, multi-path fading, and shadowing—challenge classical CE and how hybrid RIS integration, sensor fusion, and stochastic analysis have been mobilized to address them. The second, *Beam-Tracking/Beamforming Schemes*, reviews how these estimated parameters are then exploited to maintain robust beam alignment in highly dynamic UAV-ISAC environments, covering predictive filtering, multi-modal data fusion, deep-learning-based prediction, and near-field extensions [92].

##### 1) CHANNEL/TARGET ESTIMATION SCHEMES

Effective CE in UAV-ISAC systems must contend with a set of interdependent impairments: UAV jitter, high 3D mobility, multipath fading, and shadowing. Early contributions addressed these challenges individually before more integrated frameworks emerged.

The first body of work targets hardware-augmented CE. [93] introduces a hybrid reconfigurable intelligent surface (HRIS) that combines passive phase control with active sensing elements, enabling simultaneous AoA estimation and CE via the root MUSIC algorithm without dedicating separate pilot resources. This approach demonstrates that co-designing the RIS functionality with CE—rather than treating them separately—yields marked improvements in estimation accuracy. A complementary direction is pursued in [94], which couples spatial modeling of UAV jitter with a sensor fusion framework based on the unscented Kalman filter (UKF). By jointly analyzing the sensing, communication, and attitude-control loops, this work reveals that ignoring platform motion in CE design leads to systematic bias that AoA-based methods alone cannot correct.

Building on this motivation to model platform dynamics explicitly, [95] moves to a multi-UAV setting and shows that temporal correlation across drone measurements, processed through an extended Kalman filter (EKF), significantly improves velocity estimation accuracy beyond what any single-BS configuration can achieve. The complementary study in [96] isolates the jitter mechanism itself, constructing a time-division beam-searching model that quantifies how angular oscillations degrade target angle estimation as a function of jitter amplitude and beam dwell time. Together,

these two works establish a key design principle: multi-measurement aggregation and explicit jitter modeling are not independent refinements but jointly necessary conditions for reliable CE in mobile UAV scenarios.

With the CE pipeline more clearly understood, subsequent research shifts toward joint trajectory and resource optimization. Reference [97] formalizes the coupling between CE quality—measured via CRLB—and trajectory design, showing through EKF-based ground user (GU) tracking combined with successive convex approximation (SCA) that optimal positioning can substantially relax CE error bounds while simultaneously improving the communication rate. This interplay between geometry and estimation accuracy is further exploited in [98], which extends the framework to a multi-UAV network and proposes a signal-reuse strategy: the same waveform that serves communication is recycled for target detection, with SCA jointly optimizing UAV placement and transmit power to maximize the minimum detection probability subject to SINR and collision-avoidance constraints. The progression from single-UAV, single-objective CE to multi-UAV, multi-objective joint design represents a meaningful architectural shift. Reference [99] pushes this further into the IoT domain by treating UAVs as multifunctional platforms with competing scheduling, sensing, and communication demands, and proposes a three-layer iterative algorithm that dynamically prioritizes radar estimation rate while respecting flight and scheduling constraints. Similarly, [107] introduces a multi-stage beamforming and positioning pipeline in which a wide beam first performs coarse target detection before a narrow beam refines localization, integrating SDR, SCA, and ESPRIT estimation into a unified framework that progressively tightens CRB bounds as more measurements accumulate.

A qualitatively different perspective is contributed by [100], which departs from the optimization-centric tradition and instead pursues a stochastic performance characterization of sensing-assisted aerial-to-ground communications under realistic propagation. By modeling independent but non-identically distributed (i.n.d.) shadowing via an inverse-gamma distribution, non-isotropic antenna gain patterns following a 3GPP flat-top model, and a generalized chi-square radar cross-section (RCS), the work derives closed-form expressions for the coverage probability (CP), outage probability (OP), and ergodic radar estimation rate (EREIR). A two-stage sensing-assisted beam management scheme is proposed, where UAVs first exploit sensing echoes to estimate the ground user direction and then select the best codebook beam without any pilot feedback, effectively eliminating downlink overhead. Key analytical findings reveal that shadowing severity dominates performance degradation over small-scale fading, and that i.n.d. channel statistics—which better reflect spatially distributed UAV deployments—consistently outperform idealized i.i.d. assumptions. The EREIR-CP trade-off curves further show that the sensing and communication power budgets must be carefully balanced, as allocating more power to sensing

improves detection probability but degrades communication coverage, a tension absent in purely optimization-based CE designs.

## 2) BEAM-TRACKING/BEAMFORMING SCHEMES

The estimated channel and kinematic parameters from CE feed directly into beam management, where the central challenge is to maintain spatial alignment between the UAV and the base station (BS) despite continuous motion, platform jitter, and multipath propagation.

Early solutions exploit radar-assisted prediction within an EKF framework. Reference [101] proposes a dual identity association (DIA) scheme that distinguishes communication users from radar echo sources using the ISAC signal itself, enabling rapid beamformer selection at 28 GHz without separate sensing overhead. The method demonstrates that echo-based identity resolution can cut beam association errors significantly relative to conventional pilot feedback, as validated on a hardware testbed—the only hardware-validated contribution in this subsection. A closely related approach in [104] generalizes EKF tracking to multipath channels by extracting kinematic parameters directly from MUSIC-processed echo spectra, showing that radar echoes encode sufficient information to support beam prediction even when the LoS component is intermittently obstructed.

The addition of inertial and GPS data opens a complementary estimation channel. Reference [102] demonstrates that phase and amplitude compensation using UKF-refined AoA/AoD estimates reduces beam misalignment in single-user UAV scenarios, achieving SNR gains that a feedback-only scheme cannot match in the same pilot overhead budget. Reference [103] extends this to massive MIMO by fusing wireless CSI with UAV orientation and positional data from onboard sensors, revealing that the two modalities are complementary: wireless data captures short-term channel fluctuations while sensor data provides reliable kinematic predictions across longer intervals. The structural lesson from this body of work is that EKF/UKF-based predictive beamforming and sensor fusion are mutually reinforcing rather than competing design choices.

As operating frequencies rise toward the THz band, antenna rotation and near-field effects introduce new sources of beam misalignment that classical far-field methods cannot handle. Reference [105] addresses THz-band UAV communications by training a dual deep neural network (DNN) to simultaneously predict the optimal beam direction and GBS association while compensating for antenna rotation-induced AoD offsets. Compared to model-based EKF approaches, the data-driven framework proves more robust to the non-convex beam-gain surfaces that arise from electrically large arrays at THz frequencies. At the network level, [106] designs centralized and distributed cooperative beamforming for a multi-cell anti-UAV ISAC network, formulating the problem as signal-to-clutter-plus-noise ratio (SCNR) maximization subject to intra-cell, inter-cell, dual-functional, and residual

self-interference constraints, solved through AO and SCA. The multi-cell perspective is important because inter-cell interference becomes the binding constraint when individual cell-level SCNR is already optimized, a regime that single-cell beamforming designs systematically overlook. Reference [107] bridges the gap between CE and beamforming by coupling a multi-stage localization pipeline with beamformer design, showing that iterating between position refinement and beam update across wide and narrow beam stages yields substantially lower target RMSE than single-stage approaches, at the cost of increased uplink overhead.

The most recent extension reaches into the near-field regime. Reference [108] considers a BS equipped with an extremely large-scale uniform linear array (XL-ULA) that places a flying UAV within the Fresnel region, where the planar-wave assumption of conventional far-field beamforming breaks down. A sensing-assisted near-field beam tracking (SANB) algorithm is proposed, building an EKF that jointly tracks both the AoA and the distance of the UAV—a two-dimensional state estimation problem absent in all far-field designs—using delay, Doppler, and MUSIC-derived angle measurements. To handle pitch-axis jitter arising from aerodynamic turbulence, a segment-based search beam tracking (SSB) algorithm partitions the candidate receive beam directions into segments centered on the two-step EKF prediction, reducing global search complexity from  $\mathcal{O}(\pi N_d/\Theta)$  to  $\mathcal{O}(N_d)$  while recovering close to the jitter-free achievable rate. The work also derives posterior Cramér-Rao bounds (PCRB) for both angle and distance estimation, establishing analytical performance floors and confirming through simulation that RMSE tracks these bounds tightly across varying array sizes.

**Summary and Lessons Learned:** Table 3 maps the progression from single-impairment CE fixes toward integrated multi-dimensional beam management systems, and reading the works collectively rather than individually reveals several design principles that individual papers cannot establish alone.

The most fundamental finding is that jitter modeling is a precondition for meaningful optimization, not a refinement to be added later. Works that treat the UAV as a mechanically stable platform—such as the early RIS-assisted CE design of [93]—achieve strong estimation accuracy in controlled settings but degrade substantially when platform motion is introduced. Explicit jitter models, whether the angular oscillation formulation of [96] or the stochastic pitch model of [108], are necessary before any trajectory or BF optimization can be meaningfully interpreted, because an optimizer that ignores jitter will produce solutions that are locally optimal under a false premise. This observation carries forward into beam management: as demonstrated by [108], beam misalignment under jitter actually grows with the number of antenna elements, which is counterintuitive and has direct consequences for the large-array configurations that 6G systems target.

Building on this, the literature consistently shows that multi-measurement fusion outperforms single-source estimation, though the choice of fusion architecture has its own implications. EKF-based temporal aggregation [95], GPS/IMU sensor fusion [103], and codebook-echo fusion [100] all outperform their single-source counterparts, yet each carries a different CSI requirement and signaling overhead. Model-based EKF fusion assumes available CSI and performs best under moderate UAV mobility, while the stochastic analytical framework of [100] eliminates pilot overhead entirely by leveraging radar echoes for beam alignment—a trade-off that becomes progressively favorable as the number of users or the sensing update rate increases. A related finding from the same work is that shadowing severity dominates performance degradation over small-scale fading in aerial links, with the inverse-gamma shaping parameter proving nearly three times more influential than the Nakagami- $m$  fading order under severe shadowing. This result challenges the widespread practice of evaluating CE schemes under Rayleigh or Rician fading alone, and suggests that shadowing-aware CE and beam selection should be treated as a standard design requirement rather than an optional extension.

Regarding algorithmic strategy, the evidence indicates that model-based optimization and data-driven methods are complementary rather than competing. AO/SCA-based designs [97], [98], [106] provide convergence guarantees and interpretable solutions but degrade when CSI is imperfect or channel dynamics are rapid. DNN-based BF [105] generalizes better to unseen channel realizations but requires offline training data and lacks formal convergence bounds. Hybrid architectures—in which EKF predictions serve as input features to a DNN rather than a standalone controller—represent an underexplored middle ground that could inherit the robustness of both paradigms. Finally, the transition to near-field propagation in XL-ULA configurations changes the estimation problem dimensionally: distance becomes an additional trackable state alongside angle, as demonstrated in [108], rather than a fixed parameter. This near-field extension of sensing-assisted beam tracking is technically richer but also more computationally demanding, and its extension to multi-UAV swarms—where inter-UAV interference couples the individual tracking problems—remains an open problem of direct practical relevance.

Several directions emerge from these observations as particularly important for future research. DRL-based CE and trajectory co-design could improve robustness under non-stationary interference and rapid channel fluctuations that deterministic EKF models cannot track. Multi-cell beam tracking that jointly maximizes sensing SCNR and communication QoS under imperfect CSI in i.n.d. shadowing environments has received little attention. Joint waveform and BF co-design that simultaneously balances sensing resolution, SE, and platform energy consumption under realistic aerodynamic flight profiles is essential for practical

deployment at scale, and connects naturally to the EE frameworks reviewed in Subsection III-E.

## B. OPTIMIZING SYSTEM THROUGHPUT UNDER SENSING AND OTHER CONSTRAINTS

Maximizing communication throughput in UAV-ISAC systems is inherently a constrained multi-objective problem: every additional watt diverted toward sensing tightens the power budget available for communication, every sensing constraint narrows the feasible beamforming set, and every waypoint in a UAV trajectory must satisfy both aerodynamic limits and coverage demands. This subsection traces how the field has responded to these intertwined pressures, progressing from single-UAV beam-pattern designs through multi-UAV coordination frameworks and finally to RIS-augmented and AI-driven architectures. The works can be grouped around the sensing metric they employ to impose the sensing constraint, which itself carries important architectural implications: beam-pattern gain-based designs, Cramér-Rao lower bound (CRLB)-based designs for range, velocity, and position estimation, and SNR/rate-based designs.

### 1) SENSING BEAM-PATTERN GAIN-BASED DESIGNS

Beam-pattern gain as a sensing metric offers a clean geometric proxy for sensing coverage: by requiring the transmitted beam to maintain a minimum power level in the direction of interest, it implicitly regulates the fraction of degrees of freedom consumed by sensing. The foundational tension here is between spatial multiplexing gain and sensing directivity.

Reference [109] exposes this tension cleanly by considering both a quasi-stationary UAV at an optimized hover position and a fully mobile UAV. The key finding is that trajectory freedom—even a single additional degree of freedom in hover location—yields substantial throughput gains because the UAV can position itself to equalize the path-loss asymmetry between communication users and the sensing target. The non-convex joint optimization over position and beamforming is resolved via alternating optimization (AO) and successive convex approximation (SCA), producing sub-optimal solutions that nonetheless substantially outperform fixed-deployment benchmarks.

The integrated periodic sensing and communication (IPSAC) paradigm introduced in [110] advances this by making sensing frequency itself an optimization variable. A penalty-based two-layer algorithm derives a tight closed-form lower bound for the achievable rate and reveals a structural symmetry in the optimal solution: when location constraints are absent, the optimal ISAC frames exhibit a rotational symmetry that enables highly efficient algorithm design. Reference [111] extends this further by providing a closed-form solution for the optimal transmit precoder at any UAV position, decoupling the precoder design from the trajectory search and thereby making large-scale trajectory optimization tractable. The key architectural insight from the IPSAC line of work is that sensing timing is as important an optimization variable as beamforming: decoupling sensing

and communication time slots can be strictly suboptimal, but co-optimizing them recovers a significant portion of the theoretically achievable rate.

The introduction of movable antenna arrays in [112] adds a spatial reconfiguration dimension absent in all prior fixed-array designs. By treating a UAV as a low-altitude platform (LAP) carrying a movable antenna array, the work jointly optimizes transmit beamforming, sensing beamforming, and the physical positions of antenna elements, all within a single AO plus particle swarm optimization (PSO) framework. The core trade-off revealed is that antenna repositioning can substitute for trajectory changes in scenarios where UAV mobility is constrained, but at the cost of higher mechanical complexity and convergence sensitivity.

A qualitatively new level of constraint fidelity is introduced in [113], which is the first in this category to incorporate both three-degree-of-freedom (3-DoF) and six-degree-of-freedom (6-DoF) dynamic models of UAV flight. Prior beam-pattern gain designs implicitly assume that any desired trajectory is mechanically achievable; this work shows that physical controllability constraints—roll, pitch, yaw rates, and their coupling—can make nominally optimal trajectories infeasible. The joint beamforming and trajectory problem is decomposed via an AO framework in which the beamforming subproblem is convexified through SCA and semidefinite relaxation (SDR), while the trajectory subproblem is reformulated as an optimal control problem solved via control parameterization and sequential quadratic programming (SQP). The central finding is that the performance loss from incorporating dynamics is negligible relative to the feasibility gain: control-aware designs achieve trajectories that can actually be flown, whereas control-unaware optimal trajectories often cannot.

## 2) SENSING RANGE, VELOCITY, AND POSITION ESTIMATION CRLB-BASED DESIGNS

While beam-pattern gain measures what fraction of power reaches the target direction, CRLB-based designs measure how precisely the system can estimate target parameters given that power. The distinction matters because a high beam-pattern gain toward a target does not guarantee high estimation accuracy if the waveform lacks range or Doppler resolution, whereas CRLB constraints force the joint waveform-trajectory design to account for both.

Reference [114] establishes an important waveform-level baseline by showing that orthogonal time-frequency space (OTFS) modulation, deployed in a full-duplex in-band configuration, simultaneously improves Doppler robustness for vehicle tracking and reduces cyclic prefix overhead relative to OFDM. The practical implication is that waveform choice at the physical layer—not just beamforming and trajectory at the signal processing layer—significantly affects the sensing-communication trade-off region. Similarly, [115] addresses the often-neglected question of how user mobility statistics should influence resource allocation, demonstrating that

mobility-aware user-UAV association policies can substantially improve average sum rate without additional hardware.

Reference [116] pushes waveform diversity further by proposing orthogonal chirp division multiplexing (OCDM), which assigns chirp subcarriers to sensing and OFDM-like subcarriers to communication, thereby simplifying the hardware architecture for resource-limited UAVs while improving simultaneous range and velocity estimation. The trade-off identified is that OCDM sacrifices some spectral flexibility relative to adaptive OFDM but gains hardware simplicity and interference isolation between sensing and communication subcarriers.

Several works then layer trajectory and beamforming optimization on top of these waveform foundations. Reference [117] addresses a multi-UAV cell-free MIMO ISAC network, where UAVs share the sensing and communication burden. The AO plus extended Kalman filter (EKF) framework shows that distributed UAV cooperation can resolve target ambiguities that any single UAV would face due to limited aperture and observability, but at the cost of requiring tight inter-UAV synchronization. Reference [118] focuses the sensing objective on radar estimation rate—the information-theoretic counterpart of CRLB—and jointly optimizes beamforming, trajectory, and time allocation through AO, revealing that sensing and communication time fractions must be adapted not just to channel conditions but also to the instantaneous target geometry relative to the UAV.

For position estimation specifically, [119] models 3D object state transitions and formulates a strictly convex power allocation problem between the UAV and the base station (BS), yielding a closed-form unique solution. The strict convexity result is significant because it guarantees global optimality—a rare property in joint sensing-communication designs—and arises from the specific structure of the 3D state transition model. Reference [76] approaches the same position estimation objective from an adaptability angle, proposing a framework in which sensing duration is allocated on demand rather than fixed to the communication frame, so that the UAV performs sensing only when required and otherwise devotes the full time slot to communication. This sensing-on-demand philosophy recovers significant throughput without sacrificing positioning accuracy. Reference [120] then replaces the model-based AO with a deep deterministic policy gradient (DDPG) agent that learns to jointly control UAV trajectory and NOMA power allocation, achieving superior performance in environments with uncertain target mobility and latency constraints—conditions under which the fixed-model assumptions of [76] and [119] degrade.

Two new frameworks extend CRLB-based designs to richer system architectures. Reference [121] integrates a passive RIS mounted on a UAV into a NOMA-ISAC system, where the UAV acts as a mobile aerial RIS rather than a conventional transceiver. By jointly optimizing UAV trajectory, BS beamforming, and RIS phase shifts through an AO framework combining SDR and SCA, the system exploits the UAV's positional flexibility to establish reflective links

that compensate for blocked direct paths. Crucially, the work formulates a worst-case robust optimization under discrete phase quantization and bounded CSI errors, showing that 2-bit phase quantization incurs negligible AAR loss relative to ideal continuous phases—a practically important finding for hardware-constrained deployments. Reference [122] takes a full-duplex (FD) approach in which the UAV simultaneously transmits to downlink users and receives uplink signals while maintaining sensing SINR, using an AWMMSE-based beamformer within a joint communication scheduling, beamforming, and trajectory optimization (JCBTO) framework. The FD architecture improves spectral efficiency but introduces strong self-interference, which the SIC-aware beamformer must suppress; simulation results show that the FD design substantially outperforms its half-duplex counterpart in average sum rate while meeting sensing constraints.

### 3) SENSING SNR AND RATE-BASED DESIGNS

SNR-based sensing constraints are the most commonly adopted in the literature because they are tractable and directly tied to detection probability through classical radar theory. However, as the sensing constraint tightens, the feasible region for communication beamforming shrinks rapidly, so the choice of algorithm for navigating this region has significant performance implications.

Reference [123] is among the first to show that DRL can outperform AO in this regime. A proximal policy optimization (PPO)-based DRL agent jointly adapts beamforming, RIS phase shifts, and UAV trajectory to maximize the minimum communication rate subject to a sensing SNR floor. The advantage of DRL over AO in this context is generalization: the trained policy adapts to channel variations across episodes without re-solving a non-convex program at each time step, making it better suited to fast-varying channel conditions. The limitation is the training data requirement and the difficulty of guaranteeing constraint satisfaction during exploration.

Reference [124] addresses a qualitatively different scenario—emergency UAV deployment for search and rescue—where the same UAVs must simultaneously serve surviving communication users and detect trapped victims. The coordinated rate-splitting multiple access (CoRSMA)-ISAC scheme decomposes the joint optimization into UAV-user association, deployment, and beamforming subproblems, solved iteratively via K-means clustering, SCA, and SDR. By explicitly modeling the geographic separation between communication survivors and sensing targets, the work shows that CoRSMA outperforms SDMA, NOMA, and OMA under the same total power budget, primarily because rate splitting allows flexible partial interference cancellation that neither NOMA nor SDMA can achieve. Reference [125] extends multi-UAV coordination to include user-target association using matching theory (MT) and fractional programming (FP), revealing that optimal UAV-to-user assignments are sensitive to the relative positions of users and targets, and that greedy association policies can be far from optimal.

The subsequent works in this category expand the hardware palette to RIS, STAR-RIS, and reconfigurable holographic surfaces (RHS). Reference [126] integrates a DRL-based trajectory and beamforming policy for RIS-assisted low-altitude economy (LAE) scenarios, demonstrating that the combined RIS-UAV mobility provides a two-dimensional coverage enhancement—the RIS creates additional reflective paths while the UAV dynamically positions those paths—that neither alone can achieve. Reference [127] integrates multi-access edge computing (MEC) offloading into the RIS-UAV relay framework, jointly minimizing task completion time and maintaining sensing SNR, and shows that the sensing constraint acts as a binding constraint on trajectory design that can paradoxically improve communication latency by forcing the UAV to hover closer to users. Reference [128] formulates a max-min fairness problem for a UAV carrying an active RIS, accounting for the power consumed by the active amplifiers within the RIS hardware budget; the results show that active RIS provides substantially better fairness than passive RIS in scenarios with large user disparity. Reference [129] deploys RHS on UAVs in conjunction with passive RIS, showing that the holographic surface's continuous aperture control provides finer beam resolution in congested spectrum environments than a discrete phase-shift array. Reference [130] combines a STAR-RIS with a UAV relay, enabling simultaneous transmission and reflection to users on both sides of the RIS, and shows that scheduling sensing and multicast communication in alternating slots—rather than simultaneously—is preferable when the sensing target and communication users are geometrically separated.

The final group of works adopts sensing rate—the information-theoretic generalization of SNR—as the sensing metric, which captures not just whether the target is detectable but how much sensing information can be extracted per unit time. Reference [131] introduces radar mutual information (MI) as the sensing metric in a multi-UAV IoT network and imposes fairness in communication rates across IoT nodes, jointly optimizing node scheduling, power, and 3D trajectories. The interaction between fairness and sensing is non-trivial: equalizing communication rates often requires repositioning UAVs away from locations optimal for sensing, so the MI constraint directly shapes the rate-fairness trade-off. References [132] and [133] approach trajectory design from a mechanistic perspective, modeling ground user locations as a continuous density field and reformulating the trajectory optimization as a catenary shape problem within an artificial potential field (APF). This approach yields closed-form globally optimal trajectories without the path discretization that conventional AO methods require, at the cost of assuming constant user velocity. The practical lesson is that analytical trajectory solutions, when achievable, offer both global optimality guarantees and low computational complexity—properties that iterative methods cannot simultaneously provide. Finally, [134] closes the loop by combining hybrid active-passive RIS with transfer-learning-enhanced DDPG, showing that transfer

learning dramatically reduces the training overhead in new propagation environments by initializing the policy from a related scenario, making DRL-based designs more practical for deployment.

**Summary and Lessons Learned:** Table 4 covers over twenty designs published between 2022 and 2026, and a cross-paper synthesis reveals several recurring architectural patterns that individual contributions do not make explicit.

The most structurally significant finding is that the choice of sensing metric shapes the entire optimization architecture, not merely the sensing constraint. Beam-pattern gain constraints yield the most tractable formulations and suit scenarios where target direction is known but estimation accuracy is secondary. CRLB constraints introduce a coupling between waveform parameters and trajectory that beam-pattern constraints miss—a UAV at a suboptimal position can satisfy a beam-pattern constraint while delivering poor parameter estimates. Sensing rate and radar MI constraints are the most information-theoretically complete but also the most computationally demanding. The practical implication is that designers should match the sensing metric to the mission: surveillance applications where detection probability matters more than localization accuracy are well served by SNR constraints, while precision navigation and target tracking require CRLB or sensing rate metrics.

The algorithmic picture is equally instructive. AO-based methods dominate across all three subcategories because they decompose coupled non-convex problems into tractable subproblems, but their convergence to local optima becomes increasingly problematic as the number of coupled variables grows—combining trajectory, multi-user BF, RIS phase shifts, MEC offloading, and NOMA power levels within a single AO framework leads to slow convergence and local optima sensitivity. DRL-based approaches, as in [120], [123], and [126], outperform AO when channel dynamics are fast and offline policy training is feasible, but underperform when constraints must be strictly satisfied at every time step, since exploration-based training cannot guarantee constraint adherence. Hybrid approaches—using AO for structural decomposition and DRL for the hardest subproblems—represent an underexplored middle ground that warrants dedicated investigation.

A further gap that runs through nearly every design in Table 4 is the consistent undermodeling of UAV physical constraints. With the exception of [113], every design treats the UAV as a point mass with unconstrained acceleration, ignoring roll-pitch-yaw dynamics, battery depletion models, and mechanical jitter. As shown in [113], incorporating 6-DoF dynamics can make nominally optimal trajectories physically infeasible, which means that control-unaware designs solve the wrong problem. Future designs must either embed control-aware trajectory constraints from the outset or formally certify that planned trajectories are aerodynamically achievable. Similarly, imperfect CSI remains the exception rather than the norm: only [128] and [134] explicitly account

for it, despite RIS-assisted channels being among the hardest to estimate accurately. The robust design of [121] under bounded channel estimation error is an important step, and its finding that 2-bit phase quantization incurs negligible performance loss has direct hardware implications; extending this robustness to scenarios combining RIS phase uncertainty with UAV positioning error simultaneously remains open.

Several directions emerge as particularly important for future work. Multi-UAV cooperative throughput maximization under sensing constraints is largely addressed by two-stage or sequential designs; a unified framework that co-optimizes inter-UAV coordination, sensing task division, and communication load balancing would be substantially more powerful. The transition from SNR-based to sensing rate and CRLB-based constraints in RIS-augmented systems has barely begun—most RIS-ISAC designs still use SNR proxies despite the richer information available from RIS-enabled multi-path channel sounding. NOMA and RSMA have been shown to outperform OMA in sensing-constrained scenarios, but their interaction with RIS reconfigurability and UAV trajectory remains poorly characterized. Finally, energy-aware throughput maximization—where propulsion power consumed by UAV mobility is jointly minimized alongside communication power—is essential for practical deployment and connects naturally to the EE designs reviewed in Subsection III-E.

### C. WEIGHTED SUM RATE AND SENSING OPTIMIZATION UNDER CONSTRAINTS

WSR optimization in UAV-ISAC systems captures a richer objective than pure throughput maximization: by assigning distinct weights to communication and sensing performance, it allows the system designer to explicitly encode mission priorities—whether surveillance fidelity or data throughput—into a single optimization objective. This makes WSR the natural metric for scenarios where sensing and communication must be simultaneously delivered rather than traded off. As illustrated in Fig. 5, UAVs in these systems operate as dual-purpose transceivers or in cooperative configurations, and the fundamental challenge is to balance communication throughput against sensing accuracy under energy, trajectory, CSI, and hardware constraints. The works in this subsection are organized by sensing metric, since the metric choice determines not only the mathematical structure of the constraint but also which system parameters are binding and which algorithmic families are best suited.

#### 1) SENSING SE AND RATE-BASED DESIGNS

Sensing rate and SE are information-theoretic metrics that capture how much sensing information can be extracted per unit bandwidth, making them strictly more expressive than SNR thresholds in scenarios where the quality of target parameter estimation—not merely its detectability—matters.

Reference [135] is the first in this subsection to replace scalar SNR constraints with a weighted sensing SE objective,

jointly maximizing communication and sensing SE through a multi-agent reinforcement learning framework built on soft actor-critic (SAC) and multi-agent soft actor-critic (MASAC) algorithms. The central architectural contribution is the use of adaptive data augmentation during training: by artificially expanding the training distribution to cover rare channel realizations, the method achieves faster convergence and stronger generalization than standard DDPG-based approaches without additional environment interaction. The trade-off is data and compute intensity—the method requires a large offline training corpus and is less suited to scenarios where channel statistics shift frequently. Reference [136] takes a structurally different route by deploying robotic aerial base stations (RABS) on a grid and formulating a mixed-integer linear programming (MILP) problem to maximize the minimum user satisfaction rate under cardinality constraints, solved approximately via an iterative linear programming rounding algorithm. The grid-based deployment constraint introduces combinatorial complexity that continuous trajectory designs avoid, but in exchange yields coverage guarantees over discrete geographic cells—an important property for urban rescue and infrastructure inspection scenarios.

Reference [137] contributes a stochastic analysis perspective largely absent from the preceding works, examining a UAV-assisted ISAC framework under composite fading channels that combine shadowing, Nakagami- $m$  small-scale fading, and aggregate interference. A low-complexity UAV selection policy based on large-scale fading is proposed, analytically evaluating outage probability, coverage probability, detection probability, and ergodic radar estimation information rate (EREIR) in closed form. The key design insight from this work is that bandwidth partitioning between sensing and communication is the primary lever for controlling the sensing-communication trade-off: increasing the sensing bandwidth improves detection probability but directly reduces communication coverage, and this trade-off is shaped by the shadowing severity in a non-linear way that simple SNR-based analyses cannot reveal. Shadowing dominance over small-scale fading—established analytically here—aligns with findings from the CE subsection and reinforces the case for shadowing-aware system design as a standard requirement rather than an optional refinement.

## 2) POSITION ESTIMATION CRLB-BASED DESIGNS

CRLB-based sensing constraints link the optimization directly to the precision of target parameter estimation, imposing a fundamental physical limit on what trajectory and beamformer combinations can actually achieve. The works in this category share a common trajectory-estimation coupling: a UAV's position relative to the target determines the Fisher information it can collect, so trajectory design and estimation accuracy are inseparable.

Reference [138] establishes this connection for a single rotary-wing UAV by formulating a weighted optimization that jointly minimizes CRLB for target position and maximizes communication rate via a multi-stage trajectory design

and gradient descent. The central finding is that the optimal trajectory for sensing—which positions the UAV to maximize the Fisher information gain—typically conflicts with the optimal trajectory for communication—which minimizes path loss to ground users—and the weighted objective yields a family of Pareto-optimal trajectories parametrized by the sensing-communication weight. Reference [139] extends this to incorporate user bandwidth allocation alongside trajectory design, showing that jointly optimizing spectrum partitioning and trajectory under energy constraints further expands the achievable sensing-communication rate region relative to designs that fix the bandwidth split. Both works assume deterministic user and target locations, leaving open the question of how their trajectory solutions degrade under positional uncertainty.

Reference [140] addresses the UAV mobility challenge through a deep reinforcement learning (DRL) agent operating in a simultaneous transmitting and reflecting surface (STARS)-aided UAV network, where the STARS provides additional degrees of freedom for spatial beamforming without the half-space limitation of conventional RIS. The DRL agent jointly optimizes UAV trajectory, transmit beamforming, and STARS reflection-transmission coefficients to maximize a weighted combination of communication SINR and radar estimation accuracy. By learning a non-myopic policy that anticipates future channel states, the DRL approach outperforms AO-based methods under rapidly varying target dynamics—precisely the regime where the deterministic gradient descent of [138] degrades. Reference [141] introduces a fundamentally different optimization engine by deploying a large language model (LLM) as a multi-objective decision-making agent. The LLM generates candidate beamforming, trajectory, and scheduling solutions by reasoning over the system state description in natural language, demonstrating strong generalization to environments not encountered during training—a property that distinguishes it from DRL methods that require retraining when the reward landscape changes. The practical limitation is interpretability and constraint satisfaction: LLM-generated solutions may violate hard constraints in ways that a penalized DRL agent or an AO method would not.

Reference [142] scales the CRLB-based framework to a cooperative multi-UAV network with simultaneous multi-user communication and multi-target sensing. The dual-objective formulation—maximizing communication sum rate while minimizing the trace of the CRB matrix—captures a genuine Pareto trade-off surface rather than collapsing it into a single weighted scalar. The SC-DO-MUOA algorithm, built on decomposition-based evolutionary optimization and a hybrid PSO-GA solver, efficiently explores this surface, revealing that dense multi-UAV cooperation substantially reduces CRB at the cost of inter-UAV interference, and that user-target association is a critical design variable: assigning users and targets to UAVs sub-optimally can degrade both sensing and communication performance by several decibels.

### 3) SENSING SNR AND POWER-BASED DESIGNS

SNR-based sensing constraints remain the most widely adopted in the WSR category because the Neyman-Pearson detection framework directly maps SNR to detection and false-alarm probabilities, providing a hardware-interpretable guarantee. The designs in this group increasingly augment the basic SNR constraint with hardware considerations—wireless power transfer (WPT), RIS phase quantization, PAPR limits, and low-altitude economy (LAE) coverage requirements—that closer reflect practical deployment.

Reference [143] introduces WPT as an additional function alongside sensing and communication, jointly optimizing radar waveform, uplink power allocation, UAV trajectory, and time scheduling via fractional programming and majorization-minimization (MM). The interaction between WPT and sensing is constructive in narrow regimes: a strong downlink beam for energy delivery also increases the sensing echo return, so the three functions can be co-designed to reinforce rather than compete with each other. The assumption of perfectly synchronized sensing and communication phases, however, limits applicability when propagation delays are heterogeneous. Reference [144] addresses a more common scenario by focusing on a RIS-assisted DofRC UAV, jointly maximizing the weighted average of communication beamforming gain and sensing SNR through AO over trajectory, RIS phase shifts, beamforming, and user scheduling. The key finding is that user scheduling—deciding which users receive service in which time slots—is as important as beamforming in determining the WSR, because it controls the interference seen by the sensing receiver from communication signals in full-duplex configurations.

References [145] and [146] then compare two fundamentally different algorithmic strategies for the same SNR-based WSR problem. Reference [145] deploys a multi-agent DRL framework in which specialized agents using DDPG, TD3, and PPO handle distinct sub-tasks—UAV trajectory, RIS configuration, and beamforming—in a decentralized architecture. The decentralization is key: by decomposing the joint action space across agents, the framework avoids the curse of dimensionality that plagues single-agent DRL in high-dimensional UAV-RIS-beamforming problems. Reference [146] instead adopts an RSMA-based model where rate splitting flexibly partitions interference into common and private message streams, combined with time division multiplexing (TDM) between sensing and communication phases. A BCD and SCA joint optimization shows that RSMA's interference management advantage over NOMA and OMA is most pronounced when sensing constraints are tight, because RSMA can allocate the common message to absorb sensing-induced interference in a way that fixed-rate NOMA cannot. The comparison between [145] and [146] illustrates the DRL-versus-AO trade-off in a particularly clear setting: DRL generalizes better across channel realizations but cannot guarantee constraint satisfaction; AO guarantees

local optimality and constraint adherence but requires resolving at each channel realization.

Sensing power as a metric—measuring the total received echo power rather than SNR—is examined in [147], which formulates a joint UAV deployment and precoder optimization problem for simultaneous multicast delivery and target sensing. The mean-shift-based user grouping and two-layer penalty-based SCA reveal that grouping users geographically, rather than by channel gain alone, significantly improves the sensing power achievable at a given communication rate, because geographically clustered user groups produce UAV hover positions closer to sensing targets. Reference [148] brings in PAPR awareness as an additional practical constraint, since high PAPR signals stress UAV power amplifiers and reduce their effective transmit power. The MCI-ADMM framework with augmented Lagrangian and manifold optimization shows that jointly controlling PAPR, beam pattern mismatch (BPM), and multi-user interference (MUI) leads to a three-way trade-off: reducing PAPR tightens the feasible beamforming set, increasing BPM; reducing BPM requires higher peak power, increasing PAPR; and minimizing MUI redistributes power away from sensing directions, increasing BPM. This three-way coupling is invisible to designs that handle these constraints separately.

Reference [149] addresses a coverage gap specific to LAE scenarios: conventional BS antenna downtilt is optimized for terrestrial users and provides poor signal strength at UAV altitudes, so sensing UAVs at height face a structural SNR deficit. A hybrid active-passive RIS architecture overcomes this by combining the coverage of passive reflection with the amplification of active elements, jointly optimizing BS beamforming and RIS phase shifts through a mixture-of-experts proximal policy optimization (MoE-PPO) DRL framework. The MoE architecture decomposes the policy into specialized sub-networks gated by a learned router, which is better suited than a monolithic DRL policy to the structurally heterogeneous action space combining continuous beamforming with discrete phase shifts. The result—significant sensing SNR improvement and faster convergence relative to conventional DRL—validates expert decomposition as a practical strategy for high-dimensional UAV-RIS-ISAC problems.

**Summary and Lessons Learned:** An examination of the fifteen WSR-sensing co-designs summarized in Table 5 reveals a coherent research trajectory spanning 2023 to 2026, from which several recurring architectural principles can be distilled.

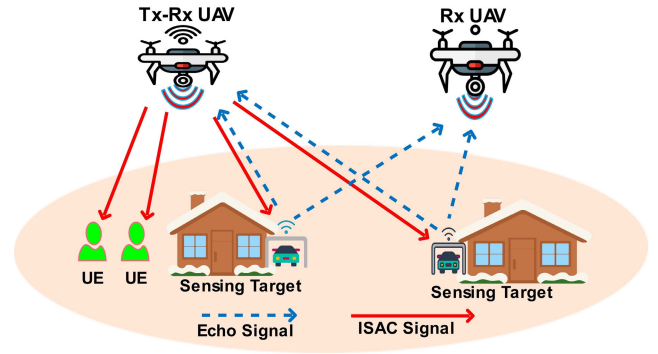
A central finding is that the sensing metric determines which system parameter becomes the binding constraint, with direct consequences for algorithm and hardware selection. When sensing rate is the metric, BW allocation is the primary optimization lever and trajectory plays a secondary role. When CRLB is the metric, trajectory becomes dominant because it directly controls Fisher information. When sensing SNR is the metric, BF and RIS configuration dominate. This metric-to-parameter coupling is not merely a mathematical

observation—it has concrete design implications: engineers should select the sensing metric that aligns with the parameter they can most flexibly control in a given deployment, rather than defaulting to SNR proxies because they are computationally convenient.

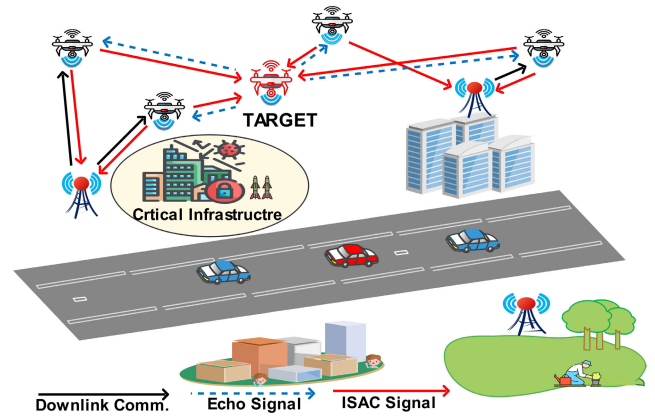
The choice of algorithm is equally consequential. AO outperforms DRL on constraint satisfaction while DRL outperforms AO on generalization, and this trade-off is illustrated most directly by the contrast between [145] (multi-agent DRL) and [146] (BCD-SCA AO): the DRL approach adapts better to unseen channel conditions but cannot provide per-sample constraint guarantees, while AO provides local optimality certificates but requires re-solving at every channel realization. The LLM-based approach of [141] introduces a third point in this space—strong zero-shot generalization but uncertain constraint adherence—that warrants further investigation as LLM inference becomes computationally cheaper. Together, these observations reinforce the conclusion from Section III-B that hybrid architectures combining AO for structural decomposition and DRL for adaptive subproblem refinement remain underexplored.

Two further gaps emerge from the hardware and channel modeling perspectives. First, shadowing and composite fading consistently dominate SNR-based performance, yet most designs in Table 5 assume Rayleigh or Rician fading without shadowing. The stochastic analyses of [137], corroborated by the CE subsection, show that shadowing severity shapes the WSR-sensing trade-off more strongly than small-scale fading parameters, and extending CRLB and SNR-based optimization frameworks to composite fading channels remains an important open problem. Second, hardware imperfections introduce binding constraints that idealized designs systematically ignore. The PAPR analysis of [148], the discrete phase quantization robustness of [149], and the power amplifier coupling in [143] collectively demonstrate this. The finding of [149] that 2-bit phase quantization incurs negligible performance loss relative to continuous phases is particularly useful: it establishes a practical hardware design point below which performance degrades substantially.

Several directions emerge as most pressing for future research. The joint optimization of sensing metric, access protocol, and hardware architecture—simultaneously selecting between NOMA and RSMA, passive and active RIS, and AO and DRL—is largely unexplored; most designs fix two of these three dimensions and optimize only the third. Pareto-optimal WSR-sensing trade-off characterization in multi-UAV networks, as initiated in [142], should be extended to account for imperfect CSI and UAV positional uncertainty simultaneously. The integration of WPT, sensing, and communication into a unified three-function optimization under realistic energy harvesting models and channel uncertainty remains an open problem of significant practical relevance for battery-limited UAV deployments. Finally, the dominance of shadowing identified here motivates developing WSR frameworks that explicitly incorporate shadowing statistics into trajectory and BF co-design, bridging the gap



**FIGURE 5.** An illustration of a UAV-based ISAC system where UAVs simultaneously communicate with the UEs and sense the targets. The same UAV can transmit joint communication and sensing signals and receive sensing echoes from the targets (left Tx-Rx UAV). Alternatively, the receiver UAV could be a separate UAV dedicated to receiving the sensing echoes (right Rx UAV).



**FIGURE 6.** An illustration of the ISAC system that allows S&C to occur simultaneously and in collaboration with surrounding nodes/infrastructure significantly decreases the sensing delay.

between the analytical channel models of Section III-A and the optimization frameworks of this subsection.

#### D. DELAY AND AOI REDUCTION

Sensing and communication functions in UAV-ISAC systems share not only hardware and spectrum but also time: every second the UAV spends transmitting a sensing echo is a second not spent relaying data, and every trajectory segment optimized for communication coverage is one not optimized for sensing geometry. This inherent time-resource coupling makes delay and AoI critical performance dimensions that throughput-centric designs systematically undervalue. AoI, defined as the elapsed time since the last successfully received status update, captures information freshness rather than raw throughput—a distinction that matters deeply in time-sensitive missions such as target tracking, disaster response, and autonomous navigation, as illustrated in Fig. 6.

The body of work surveyed here progresses from early signal-level delay reductions through network-layer stochastic analysis and into trajectory-level AoI optimization, with each generation addressing limitations left open by the previous one.

The earliest contributions in this space target delay at the signal processing level. Reference [150] fuses communication-based location data with radar echo information through an EKF and introduces an ISAC-based identification friend or foe scheme that performs radar sensing and communication interrogation simultaneously rather than sequentially. The simultaneous operation is the key innovation: by eliminating the time-division between sensing and interrogation, the scheme reduces sensing time and thereby communication delay by up to 50%, while improving target sensing accuracy by 24.2%. The central design principle demonstrated here—that co-scheduling sensing and communication functions within the same time slot can simultaneously reduce delay and improve sensing quality—motivates the more complex joint optimization frameworks that follow.

Reference [151] moves the analysis from the signal level to the network layer, where delay violations arise not from processing latency but from queuing, packet loss, and stochastic channel fluctuations. By modeling UAVs as a Poisson cluster process (PCP) and applying stochastic network calculus (SNC), the work derives closed-form expressions for the delay violation probability and the sensing-communication trade-off as a function of power allocation. The antenna misalignment analysis is particularly instructive: even moderate angular deviations between UAV and ground receiver reduce the effective link SNR enough to push delay violation probabilities above acceptable thresholds, suggesting that beam alignment and delay management must be co-designed rather than treated independently.

Emergency deployment represents a qualitatively different operating regime, where the time budget for optimization is itself constrained. Reference [152] addresses this by separating the optimization problem into offline and online stages. In the offline stage, a dynamic particle swarm optimization (DPSO) algorithm generates a comprehensive UAV deployment dataset that is used to train a convolutional neural network (CNN). In the online stage, the trained CNN replaces DPSO entirely, producing near-optimal deployment decisions in milliseconds rather than minutes. The result is that localization accuracy and communication throughput are jointly maintained in real-time without the computational overhead of re-running DPSO at each decision point. This offline-training/online-inference paradigm represents a general strategy for latency-critical ISAC deployment that goes beyond the specific emergency scenario.

The majority of subsequent works shift the objective from delay minimization to AoI minimization, recognizing that information freshness is a more mission-aligned metric for UAV sensing systems. Reference [153] tackles AoI in terrain-obstructed environments—specifically remote mountainous regions—where the UAV must balance trajectory decisions between maintaining sensing geometry and sustaining communication links. A dynamic programming framework exploits the UAV’s geometric relationship with targets and ground stations, yielding a trajectory policy that reduces

communication AoI while preserving positioning accuracy. The finding that random trajectories lead to substantially higher AoI than optimized ones underscores that trajectory is the primary AoI lever in terrain-complex environments, more so than power or scheduling.

References [154] and [155] form a complementary pair that together cover single-target and multi-target peak AoI (PAoI) minimization. Reference [154] derives a semi-closed-form optimal UAV position for the single-target case via Newton’s iterative method—a rare analytical tractability result in UAV-ISAC optimization—and then generalizes to multiple targets through SCA. The analytical solution reveals that the optimal hover position is not the geometric midpoint between the communication user and the sensing target but is biased toward whichever function has the tighter AoI constraint, providing a principled rule for UAV positioning under mixed sensing-communication objectives. Reference [155] addresses the multi-target regime through a joint trajectory-scheduling-power allocation framework, showing that SCA-based fractional programming outperforms AO in PAoI reduction because it can handle the non-convex coupling between target scheduling order and power allocation in a single iteration rather than alternating between them.

Reference [156] introduces the most complete formulation in this subsection by jointly treating data volume, AoI, sensing quality, and UAV energy within a single mixed-integer nonlinear programming (MINLP) problem. The key design variable is operating frequency: by selecting different frequency bands for different sensing tasks, the UAV can trade sensing resolution for EE, enabling it to sustain operation longer and thereby serve more targets before battery depletion. The five-stage AO decomposition that solves the MINLP produces a schedule that adapts sensing duration, transmit power, and frequency on a per-target basis—a level of operational flexibility absent from all earlier AoI designs. Another work [157] extends AoI-aware ISAC to the demanding high-speed rail (HSR) context, where Doppler shifts, frequent handovers, and reliability requirements for safety-critical train control systems impose constraints qualitatively different from those in static or pedestrian scenarios. A hybrid PSO-GA algorithm jointly optimizes bandwidth allocation, transmit power, and UAV location under both latency and reliability constraints, showing that the HSR mobility profile creates a time-varying feasibility boundary that neither pure PSO nor pure GA can navigate efficiently on its own, but their combination can. The use of radar mutual information rather than SNR or AoI as the sensing metric is notable: it captures both detection probability and parameter estimation quality simultaneously, making it particularly appropriate for scenarios where the radar must simultaneously detect the train’s presence and estimate its position and velocity.

**Summary and Lessons Learned:** The eight designs catalogued in Table 6 span from 2021 to 2025 and collectively trace a progression from signal-level delay reduction toward network-layer and trajectory-level AoI optimization, from which several cross-cutting design principles can be distilled.

The most operationally impactful finding is that co-scheduling sensing and communication within the same time slot consistently outperforms time-division separation. The 50% delay reduction demonstrated in [150] sets a benchmark that subsequent works implicitly target: every design that assigns sensing and communication to orthogonal time slots sacrifices the time-multiplexing gain that simultaneous operation provides. The MINLP framework of [156] is the most explicit about this, showing that joint scheduling within each time slot—rather than alternating between sensing-only and communication-only phases—yields both lower AoI and higher data volume simultaneously, demonstrating that the two objectives are constructively rather than adversarially coupled in this respect.

The dominant AoI optimization lever, however, depends fundamentally on the deployment geometry. In terrain-complex environments, [153] demonstrates that the UAV's path determines AoI more than any scheduling or power allocation choice, because terrain obstructions make certain trajectories infeasible for sensing regardless of how resources are allocated. Conversely, [155] shows that in multi-target flat environments, the ordering in which targets are visited—the scheduling problem—is more influential than the specific trajectory between waypoints. This geometry-dependence has direct implications for algorithm selection: terrain-complex deployments benefit most from trajectory optimization methods, while dense multi-target surveillance benefits most from combinatorial scheduling solvers. These two approaches are not interchangeable, and applying the wrong one to a given deployment will yield substantially suboptimal AoI performance.

Regarding the computational feasibility of these designs in time-critical scenarios, [152] demonstrates that CNN-based online deployment decisions can match DPSO quality while reducing decision latency by orders of magnitude. The offline-training/online-inference paradigm underlying this result is broadly applicable: any UAV-ISAC scenario where the optimization problem structure is stable but the specific channel and position parameters change rapidly is a natural candidate. The open question is robustness to distribution shift—when the online environment departs significantly from the offline training distribution, CNN decisions can degrade rapidly, and mechanisms for detecting and correcting this drift remain underdeveloped.

Several directions emerge as particularly important for future research. None of the works in Table 6 incorporate security-aware delay constraints: an adversary who jams the sensing link can artificially inflate AoI, so delay-optimal designs that ignore jamming are structurally fragile. Multi-hop UAV communication networks, where sensed data must be relayed through intermediate UAVs before reaching the ground station, introduce AoI dynamics not captured by the single-hop models used throughout this subsection. Energy-AoI trade-offs—where the UAV must choose between frequent short sensing visits (low AoI, high mobility energy

cost) and infrequent long visits (high AoI, low energy cost)—remain analytically characterized only for simplified trajectory models; realistic aerodynamic energy models of the kind developed in Subsection III-E have not yet been applied to AoI optimization. Finally, RL-based adaptive deployment strategies capable of responding in real time to unexpected channel conditions and target dynamics represent a natural next step.

## E. ENHANCING EE

EE in UAV-enabled ISAC systems is shaped by a three-way tension that does not appear in ground-based networks: propulsion power—which scales nonlinearly with airspeed and acceleration—competes with communication transmit power and sensing waveform energy for the same onboard battery. This means that trajectory choices, which are primarily a propulsion energy decision, simultaneously determine the channel quality seen by sensing and communication functions, coupling all three energy consumers into a single joint optimization. The works surveyed here address this coupling through two complementary lenses. The first group, reviewed in the Sensing Distance, SINR, Angle, and Position-Based Designs subcategory, exploits geometric and positional degrees of freedom to reduce propulsion and transmit energy simultaneously. The second group, reviewed in the Sensing Information Rate, Mutual Information, and Latency-Based Designs subcategory, applies information-theoretic sensing metrics and integrates computation offloading and latency management into the EE objective.

### 1) SENSING DISTANCE, SINR, ANGLE, AND POSITION-BASED DESIGNS

The earliest contributions in this group recognize that propulsion energy and communication energy are not independent: a UAV that positions itself closer to a ground user reduces transmit power requirements, but may simultaneously degrade the sensing geometry. The central design question is therefore not how to minimize any single energy component but how to jointly shape the trajectory to minimize their weighted sum.

Reference [158] establishes this theme in a vehicle-to-everything (V2X) context, proposing an energy-efficient computation offloading strategy where sensing data from multiple vehicles is fused at the UAV before transmission. The SCA-based formulation shows that jointly optimizing task offloading decisions and resource allocation—rather than treating computation and communication energy separately—reduces total latency and energy consumption simultaneously, because offloading heavy computation tasks to the edge server relaxes the UAV's onboard processing load and allows it to reduce hover time near high-computation zones.

Reference [159] extends the geometric intuition by introducing a flight-hover communication protocol in which the UAV performs communication tasks while hovering and sensing tasks while in motion. This temporal separation

of modes is counterintuitive but effective: sensing during flight leverages synthetic aperture effects to improve radar cross-section estimation without additional transmit power, while hovering for communication maximizes beamforming gain by eliminating Doppler-induced angle estimation errors. A DRL agent learns this dual-mode policy end-to-end, demonstrating that the flight-hover assignment cannot be determined by a fixed rule but depends on the instantaneous network topology and target geometry.

Reference [160] integrates wireless power transfer (WPT) as a third function alongside sensing and communication, jointly optimizing transmit waveforms, receive filters, and power levels through AO combined with fractional programming and majorization-minimization (MM). The key coupling revealed is that sensing waveforms can simultaneously deliver energy to energy-constrained users via sidelobe radiation, so the radar waveform design problem becomes a three-way trade-off between sensing performance, communication rate, and harvested energy. Reference [161] then demonstrates that the SINR-based sensing constraint binds differently at different hover heights: at low altitudes, the dominant energy cost is hovering propulsion; at high altitudes, it shifts to transmit power needed to maintain sensing SINR. The SDR, big-M, and SCA framework used to solve the resulting MINLP problem reveals that the optimal altitude is not the lowest feasible one but a function of the target density and the communication user distribution.

Reference [162] makes the propulsion energy model explicit by addressing a synthetic aperture radar (SAR) UAV scenario, where the trajectory must maintain a minimum cross-range resolution. The SCA plus block coordinate descent (BCD) framework reduces propulsion power by 50% compared to the shortest-path trajectory, not by flying shorter distances but by selecting paths along which the SAR geometry is inherently satisfied without additional hover time. This finding challenges the intuition that minimizing path length minimizes energy: the optimal energy-efficient trajectory is the one that maximizes the sensing utility earned per unit of propulsion energy spent.

Reference [163] shifts the design variable from trajectory to antenna selection, showing that dynamically activating only the subset of antennas needed to maintain target angle estimation accuracy—computed via EKF prediction—substantially reduces circuit power consumption. The fractional programming algorithm that determines the optimal active antenna count reveals a non-monotone relationship: increasing the active antenna count beyond a threshold actually reduces EE because the marginal beamforming gain falls below the additional circuit power cost.

Reference [164] formulates the problem as accumulated sensing energy maximization subject to communication QoS, using approximate dynamic programming and semidefinite programming. The accumulated sensing energy metric—integrating the sensing power directed at targets over the mission—is more appropriate than point-in-time SNR for long-duration area monitoring missions, where

consistent sensing coverage matters more than peak performance. Reference [165] extends this to multi-charging station environments, where the UAV can recharge mid-mission. The SQP-based multi-stage path planning reveals that optimal charging schedules interleave communication tasks with recharging in a non-obvious order, because the channel quality improvement gained by positioning near users during recharge can offset the time cost of the detour.

Reference [166] introduces aerodynamic propulsion models and velocity-dependent energy consumption—absent from all prior single-UAV EE designs—into a multi-user, multi-target ISAC system with limited backhaul capacity. By jointly optimizing trajectory, velocity, beamforming, power allocation, and sensing time within an AO framework using SDR and SCA, the work shows that velocity is an under-appreciated design variable: flying faster reduces hover time near users but increases propulsion power, and the optimal velocity profile is non-constant, decelerating near sensing targets to improve estimation accuracy and accelerating between waypoints to minimize transit energy. The backhaul constraint adds a further coupling: improving communication rate beyond the backhaul capacity is wasteful, so the optimal beamformer allocates residual degrees of freedom to sensing rather than communication.

Reference [167] addresses low-altitude economy (LAE) scenarios in which unauthorized UAV detection is the primary sensing task, and ground base station (GBS) beamforming and UAV trajectories must be jointly optimized under uncertain target dynamics. The Deep Energy-efficient LAE-ISAC (DeepESC) framework uses a constrained action selection policy within a meta-learning extension (Meta-DeepESC) that employs episodic experience replay and GRU-based actor-critic networks to capture temporal correlations in target mobility. The key advance over standard DRL is the meta-learning component: by training across a distribution of flight durations and target densities, Meta-DeepESC generalizes to unseen LAE scenarios with substantially fewer adaptation steps than standard DRL, while maintaining EE and sensing robustness under imperfect CSI.

## 2) SENSING INFORMATION RATE, MUTUAL INFORMATION, AND LATENCY-BASED DESIGNS

Information-theoretic sensing metrics—radar MI and estimation information rate—capture EE more completely than SNR or beam-pattern gain, because they account for both the quality of the sensing signal and the information extracted from it per unit energy. This subcategory also integrates multi-access edge computing (MEC) and multi-layer network architectures, recognizing that computation offloading is itself an energy variable that interacts with sensing and communication power.

Reference [168] establishes the MEC-ISAC connection by formulating a joint optimization of sensing scheduling, time allocation, and trajectory to minimize UAV energy consumption while meeting radar estimation information

rate requirements. The BCD plus maximum likelihood decomposition shows that the sensing schedule—which targets are sensed in which time slots—is the most influential variable, more so than trajectory or power, because a poor schedule forces the UAV to sense targets in unfavorable geometric positions, wasting both propulsion and transmit energy.

Reference [169] introduces radar MI as a sensing fairness metric, requiring that every sensing target receive a minimum MI per time slot. The SCA and fractional programming solution reveals a fairness-EE trade-off that is qualitatively different from the communication fairness-EE trade-off: equalizing sensing MI requires the UAV to visit targets in geometrically unfavorable positions, increasing propulsion energy, whereas communication fairness can often be addressed through power reallocation without trajectory changes.

Reference [170] scales the framework to a multi-UAV swarm performing device-free vehicle sensing through MARL. The hyperparameter tuning strategy in the MARL framework reveals that the sensing MI constraint is more sensitive to the learning rate than the communication rate constraint, because MI estimation requires accurate channel characterization which is disrupted by large policy updates. This finding has implications for curriculum design in MARL: the sensing task should be introduced before the communication task in training to allow the agents to learn stable channel estimation before attempting joint optimization.

References [171] and [172] form a complementary pair that together address integrated sensing, communication, and computation (ISCC) in multi-layer network architectures. Reference [171] focuses on intelligent transportation systems (ITS), where a central UAV acts as an edge server for secondary ISCC UAVs, and an asynchronous advantage actor-critic (A3C)-based DRL algorithm jointly optimizes bandwidth, power, and computing capacity across the fleet. The asynchronous architecture is key: it allows secondary UAVs to update their policies independently without waiting for global synchronization, which is impractical at vehicular speeds. Reference [172] extends this to a space-air-ground integrated network (SAGIN), where UAVs assist in tracking mobile users while satellite backhaul handles long-range data delivery. An EKF-based prediction model and robust SDR/SCA beamforming framework address the beam misalignment that arises from the multi-layer Doppler environment, showing that service continuity in SAGIN requires explicitly predicting user positions two time slots ahead rather than relying on instantaneous channel feedback.

Reference [173] introduces adversarial robustness into the EE framework, addressing an active RIS-mounted UAV operating under jamming attacks. The Stackelberg game (SG) component models the strategic interaction between the UAV network and jammers—each optimizing against the other—while the soft double deep deterministic policy gradient (SD3) algorithm handles continuous resource

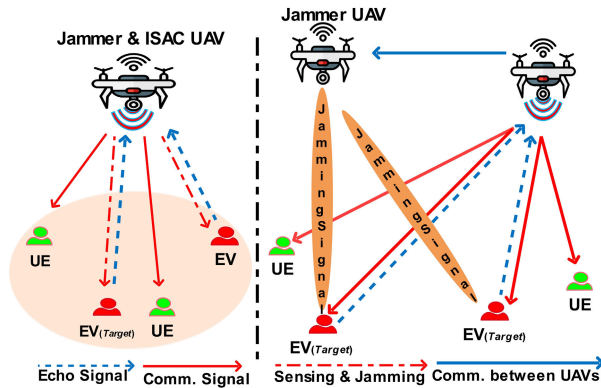
allocation decisions within the game-theoretic framework. The twin-critic architecture of SD3 reduces overestimation bias relative to standard DDPG, which is particularly important in adversarial settings where overestimating the value of a channel selection can lead to systematic exploitation by the jammer. The result is a framework that maintains both EE and sensing accuracy under sustained jamming, a capability absent from all other EE designs in this subsection.

**Summary and Lessons Learned:** The sixteen designs presented in Table 7 span from 2022 to 2026, and a systematic examination of their optimization structures yields several architectural principles that individual contributions do not make explicit.

A foundational observation is that propulsion energy and transmit energy are not independently optimizable, contrary to the implicit assumption of most designs that fix one while optimizing the other. The trajectory determines the channel geometry, which in turn determines the transmit power required to satisfy sensing and communication constraints, leaving the residual power budget for propulsion. Designs that decouple these two quantities therefore solve a structurally simpler but systematically suboptimal problem. The joint trajectory-velocity-power frameworks of [165] and [166] illustrate that co-optimization yields substantial energy savings, particularly when velocity is treated as a continuous decision variable rather than fixed at a nominal cruise speed—a modeling choice that most prior work avoids due to the resulting nonconvexity, but which [166] resolves through an AO framework combining SDR and SCA.

Building on this, the flight-hover protocol emerges as a more effective EE lever than the literature commonly acknowledges. Reference [159] demonstrates that separating sensing (performed during flight) from communication (performed during hover) can improve both functions simultaneously, because each operational mode is geometrically optimal for one task. This temporal separation is algorithmically straightforward yet frequently overlooked in favor of more complex simultaneous S&C designs. Its practical advantage is most pronounced when sensing targets and communication users are geographically separated, which characterizes the majority of surveillance and monitoring deployments.

The algorithmic dimension reveals a complementary trade-off. DRL generalizes better than AO across varying flight durations and target densities, as demonstrated by the meta-DRL framework of [167], which adapts to unseen LAE scenarios with substantially fewer retraining steps. However, standard DRL frameworks—including meta-DRL—are not inherently robust to adversarial channel conditions. Reference [173] shows that incorporating a Stackelberg game (SG) component to model adversarial channel selection resolves this vulnerability, but at the cost of requiring an explicit model of jammer behavior. Hybrid designs combining meta-DRL for generalization with SG for adversarial robustness represent a promising but largely unexplored direction. A separate constraint shift arises when MEC is



**FIGURE 7.** An illustration of secure UAV-assisted ISAC, where a single ISAC UAV also functions as a jammer (left side), or two separate UAVs coordinate for jamming and ISAC operations (right side).

integrated into the system: in MEC-ISAC frameworks such as [168] and [171], the dominant energy cost migrates from transmission to edge computation, inverting the standard EE design priority. In these systems, the scheduling of offloading decisions—determining which UAV offloads to which edge server at which time slot—matters more than trajectory or power optimization, and hierarchical frameworks that co-optimize offloading, sensing schedules, and UAV trajectories remain an important unsolved problem.

Several open directions merit immediate attention. Aerodynamic energy models that account for both velocity-dependent propulsion and jitter-induced attitude control power have been applied in [166] but have not yet been combined with MEC offloading or multi-charging-station trajectory frameworks. EE designs for LAE scenarios currently focus on unauthorized UAV detection; extending them to collaborative LAE fleets requiring joint area coverage under total fleet energy constraints is a natural and practically relevant next step. The interaction between RIS hardware power consumption—particularly for active RIS incorporating amplifiers, as in [173]—and UAV propulsion energy has not been jointly characterized in a unified framework. Finally, robust EE optimization under simultaneous CSI uncertainty and jammer presence, beyond the single-adversary scenario considered in [173], represents a natural bridge to the security-oriented designs reviewed in Subsection III-F.

## F. IMPROVING SECURITY

Security in UAV-ISAC systems is structurally more complex than in conventional wireless networks for two reasons. First, the ISAC waveform carries information about both communication users and sensing targets, so an eavesdropper who intercepts communication also learns about the sensing geometry and vice versa—a cross-domain leakage that purely communication-centric security designs cannot address. Second, the UAV's trajectory is observable from radar echoes, meaning that even a passive eavesdropper gains positional information about the UAV simply by listening. These two properties create a dual vulnerability that motivates the

security strategies surveyed here, as illustrated in Fig. 7. The works are organized by adversary complexity—single eavesdropper or warden versus multiple eavesdroppers or wardens—since this determines both the optimization structure and the algorithmic family needed.

### 1) SINGLE EVE/WARDEN-BASED DESIGNS

The single-adversary regime allows a cleaner characterization of the fundamental sensing-security trade-off, because the eavesdropper's position can be modeled precisely and the secrecy rate maximization problem reduces to a tractable bilevel structure.

Reference [174] establishes the foundational coupling between sensing and security by showing that the same EKF used for legitimate user tracking can be turned against the adversary: echo delay measurements that refine Bob's position estimate simultaneously allow the UAV to steer nulls toward the eavesdropper's predicted location. The SCA plus BCD framework reveals that trajectory is the primary security lever—repositioning the UAV to widen the angular separation between Bob and the eavesdropper yields larger secrecy rate gains than increasing transmit power. However, this trajectory-based advantage degrades when Bob's mobility is high and EKF tracking lags behind actual positions, motivating the sensor-fusion approaches reviewed in Section III-A.

RIS integration emerges as the next architectural step, providing additional spatial degrees of freedom for security without increasing UAV transmit power. Reference [175] demonstrates that a RIS-assisted UAV can simultaneously strengthen the LoS link to Bob through constructive phase alignment and introduce artificial noise toward the eavesdropper through destructive interference—two functions that consume the same RIS hardware and share the same transmitted signal. Reference [176] formalizes this by jointly optimizing UAV deployment, BS beamforming, artificial noise power allocation, and RIS phase shifts through AO, SDR, and SCA, showing that the RIS phase shift is the most sensitive variable: small errors in phase quantization degrade secrecy rate more than equivalent errors in power allocation. Reference [177] adds EE to the security objective, revealing that the optimal EE-secure trajectory differs qualitatively from the purely secrecy-optimal trajectory: the EE-aware design sacrifices some secrecy rate to reduce propulsion energy, positioning the UAV at an intermediate location that is suboptimal for both metrics individually but achieves a favorable weighted combination. Reference [178] reframes the security objective from secrecy rate maximization to CRB minimization subject to secrecy constraints, showing that these two objectives are not monotonically aligned: trajectory positions that minimize CRB often place the UAV close to the sensing target, which may also reduce the angular separation from the eavesdropper, degrading secrecy. The PSO plus SDR plus MM plus ADMM decomposition that resolves this tension is the most computationally intensive in this subcategory, suggesting that the CRB-secrecy joint

design is a fundamentally harder problem than pure secrecy rate maximization.

The next layer of sophistication addresses dual threats—systems where both communication and sensing are targeted by eavesdroppers simultaneously. Reference [179] is the first in this subcategory to model dual eavesdropping explicitly, showing that the beamformer must satisfy a more stringent constraint than in single-threat models: the information beam must be concentrated toward Bob while the sensing beam must maximize target echo SNR, and both must suppress radiation toward the eavesdropper's angular sector. The AO plus SCA plus SDR solution reveals that these three requirements can be simultaneously satisfied only when the eavesdropper, target, and user are angularly separated by at least a minimum amount determined by the array aperture. Reference [180] addresses the scenario where eavesdropper CSI is imperfect, showing through a cooperative UAV-RIS architecture that robust beamforming under bounded CSI uncertainty can maintain secrecy rates within 10% of perfect-CSI performance for uncertainty radii up to 15%—a finding that justifies the assumption of approximate CSI for the eavesdropper that most other designs make.

Reference [181] introduces a full-duplex UAV that simultaneously transmits to legitimate users and broadcasts jamming signals toward the eavesdropper, while also performing radar sensing. The BCD plus SDP framework shows that the full-duplex architecture achieves higher sum secrecy rate than either a dedicated jammer UAV or a half-duplex transmitter alone, because it eliminates the time-sharing overhead between communication and jamming. The key limitation is residual self-interference from the FD operation, which the beamformer must suppress simultaneously with the eavesdropper, making the constraint set significantly tighter than in half-duplex designs.

Reference [182] moves beyond secrecy rate to covert communications, where the goal is not just to prevent eavesdropping but to prevent detection of the transmission itself. The AO plus SCA framework reveals that covert-ness and sensing are constructively coupled: the sensing waveform that estimates target parameters also provides a cover signal that masks the communication waveform from the warden's detector, so systems that integrate sensing and communication achieve higher covert rates than those that separate them. While [183] extends covert communication to a full ISAC-IRS-NOMA framework with distributed cooperative jammers, showing that proactive jammer activation—triggered by the system's own sensing estimate of the eavesdropper's behavior—achieves substantially higher covert transmission rates than reactive jamming. The dual-phase sensing-communication design separates the frame into a sensing phase where eavesdropper behavior is predicted and a communication phase where jammers are activated based on those predictions.

Different from covert communication works [182], [183], and [184] deploys a dedicated maneuverable jamming UAV

alongside the source UAV, using a hybrid monostatic-bistatic radar model so that the jamming UAV's transmissions simultaneously disrupt eavesdropping links and contribute to target detection. The two-phase design—alternating between secure communication and joint sensing-communication-jamming—reveals that the optimal phase duration ratio depends on the target geometry and the eavesdropper's estimated mobility. Reference [185] replaces conventional RIS with a reconfigurable holographic surface (RHS) in a full-duplex ISAC system, showing that the RHS's continuous aperture control—compared to the discrete phase shifts of conventional RIS—provides finer covert rate shaping under imperfect warden CSI. The Bernstein-type inequality applied to the probabilistic detection constraints converts the robust covert optimization into a deterministic form solvable by SCA and MM without requiring Monte Carlo sampling.

## 2) MULTIPLE EVES/WARDENS-BASED DESIGNS

Multiple adversaries introduce qualitatively new challenges: the beamformer must suppress radiation toward all eavesdroppers simultaneously, and if eavesdroppers cooperate—sharing received signals to improve their joint decoding—the secrecy rate degrades faster than the number of adversaries would suggest. Practical multi-eavesdropper scenarios also rarely provide accurate CSI for all adversaries simultaneously, making robustness an essential design consideration.

Reference [187] addresses the single-eavesdropper limitation of earlier jammer-UAV designs by extending to a multi-eavesdropper network where the jammer broadcasts omnidirectional interference while the source UAV dynamically adjusts trajectory, transmit power, and user scheduling based on radar echo estimates of eavesdropper positions. The SCA solution reveals that trajectory adaptation is more effective than power increase when multiple eavesdroppers are present: increasing power benefits both legitimate users and eavesdroppers proportionally, while repositioning the UAV can improve the secrecy geometry without benefiting any eavesdropper. Reference [188] addresses a structurally different multi-adversary problem: a network of cellular-connected UAVs where the eavesdroppers are other UAVs. The detection fusion model—where sensing information is shared over cellular links—enables cooperative localization of adversarial UAVs with accuracy far exceeding what any single UAV could achieve, demonstrating that the ISAC sensing function can directly replace dedicated surveillance radar for airspace monitoring. While [189] builds on this by adding LSTM-based mobility prediction to generate predictive beamformers that pre-steer nulls toward the anticipated positions of multiple aerial eavesdroppers, achieving lower secrecy outage probability than reactive beam steering while using less pilot overhead.

Reference [190] addresses covert communications under multiple wardens, showing through a BCD-based framework that the covert rate achievable under multiple detection threats is lower-bounded by the worst-case warden's

detection probability constraint. The result is that adding a second warden with a different angular position than the first does not simply tighten the constraint—it fundamentally changes the optimal trajectory, which must now avoid the angular sectors of all wardens simultaneously rather than just one.

Reference [191] provides the most complete multi-adversary framework by combining RIS reconfigurability with robust MADRL in a setting with imperfect eavesdropper CSI. The centralized training with decentralized execution (CTDE) architecture allows multiple UAVs to develop coordinated beamforming and RIS configuration policies during offline training but execute them independently during deployment, maintaining scalability when some UAVs lose communication with the central controller. The uncertainty estimation and correction mechanism in the robust PPO algorithm explicitly accounts for CSI imperfection in the policy gradient, yielding secrecy rates that degrade gracefully as CSI uncertainty increases—a robustness property absent from all AO-based designs in this subsection.

**Summary and Lessons Learned.** A consolidated analysis of the eighteen designs in Table 8—spanning single-eavesdropper, multiple-eavesdropper, and covert communication adversary models across 2023 to 2026—reveals several cross-cutting architectural principles with direct implications for practical system design.

A finding that cuts across [174], [182], and [183] is that sensing and security are constructively coupled rather than competing for the same resources. Radar echoes provide information about the eavesdropper’s position and mobility that can directly improve BF, trajectory decisions, and proactive jamming activation—the opposite of the intuition that sensing consumes resources needed for security. ISAC designs that treat sensing and security as independent objectives therefore systematically forgo secrecy rate improvements that joint design could recover. Closely related is the observation that trajectory repositioning, RIS phase configuration, and transmit power increase are not equally effective security levers. Trajectory repositioning is primary because it changes the angular separation between the legitimate user and the adversary; RIS phase configuration is secondary because it creates additional spatial degrees of freedom without increasing radiated power; transmit power increase is the least effective because it benefits both the legitimate receiver and the eavesdropper proportionally, yielding the smallest marginal secrecy gain. Designs that allocate equal optimization effort to all three variables therefore systematically over-invest in power allocation at the expense of geometry and phase management.

The channel modeling dimension reveals a gap of substantial practical significance. The majority of single-eavesdropper designs assume perfect CSI for the adversary, which is unrealistic since a passive eavesdropper reveals no CSI to the network. Only [180] and [185] incorporate bounded or probabilistic CSI uncertainty models,

and both demonstrate that robust designs maintain secrecy within a small margin of their perfect-CSI counterparts for moderate uncertainty levels. Extending this robustness to the multiple-eavesdropper regime—where CSI uncertainty applies simultaneously to all adversaries—remains largely open and is likely to require fundamentally different problem formulations, since the worst-case uncertainty set grows combinatorially with the number of adversaries.

A further structural observation is that communication secrecy, sensing spoofing, and covert operation constitute distinct threat categories that require qualitatively different countermeasures. Communication secrecy threats are addressed through secrecy rate maximization and null-steering. Sensing spoofing threats—where an adversary injects false radar echoes or manipulates its RCS to mislead the UAV-ISAC sensing function—are not explicitly modeled in any design in Table 8, despite their practical importance in contested airspace. Covert operation threats, where the warden attempts to detect the presence of a transmission rather than decode its content, require fundamentally different metrics from secrecy rate. Designs that conflate these categories produce countermeasures that are effective against one threat type while leaving the system structurally vulnerable to the others.

Several directions emerge as most important for future research. Sensing spoofing and deception attacks have received almost no analytical attention despite their operational significance; formal adversary models and the corresponding robust ISAC waveform designs are needed. The cross-domain leakage problem—where communication symbols reveal sensing intent and vice versa—has not been formally characterized; information-theoretic frameworks for cross-domain secrecy remain an open foundational problem. The joint effect of imperfect eavesdropper CSI and UAV positional uncertainty on secrecy performance has not been analyzed, despite both sources of uncertainty degrading secrecy simultaneously in realistic deployments. Finally, QKD for UAV communications, which provides information-theoretic secrecy independent of adversary computational power, remains unexplored in the ISAC context where the sensing waveform could potentially serve as the quantum channel probe—a dual-use possibility that connects directly to the hardware and waveform design innovations reviewed across Subsections III-A through III-E.

#### IV. EMERGING CHALLENGES AND DIRECTIONS FOR RESEARCH

The detailed reviews and lessons learned presented across Section III surface a coherent set of open problems that cut across all six technical pillars of UAV-ISAC research. Rather than repeating subsection-level observations, this section consolidates and elevates the cross-cutting challenges that no single design in the literature has yet resolved, and identifies the research directions most likely to unlock practical 6G deployment of UAV-ISAC systems.

### A. REALISTIC CHANNEL AND PROPAGATION MODELING

A recurring finding across Subsections III-A and III-C is that shadowing severity dominates UAV-ISAC performance far more than small-scale fading parameters, yet the overwhelming majority of designs—including almost all optimization-based frameworks in Subsections III-B through III-F—assume Rayleigh or Rician fading without shadowing. The stochastic analyses in [100] and [137] demonstrate analytically that i.n.d. shadowing statistics, which better reflect spatially distributed UAV deployments, change both the optimal trajectory and the optimal bandwidth allocation relative to idealized fading models. Similarly, the near-field propagation regime that emerges when base stations carry extremely large-scale antenna arrays changes the sensing problem dimensionally: distance becomes a tracked state alongside angle, and the PCRB grows with array size under jitter, a counterintuitive result with direct implications for 6G massive MIMO-ISAC co-design. These high-frequency, high-mobility regimes also strain conventional matrix-based channel estimation, motivating the tensor-based formulations that exploit the multidimensional (angle–delay–Doppler) structure of the channel for joint channel and target parameter estimation [192], [193]. Future research should embed composite fading models—incorporating shadowing, near-field spherical wavefronts, and non-isotropic antenna patterns—as standard channel assumptions rather than special-case extensions, and should pair them with estimation methods, such as tensor decompositions, capable of resolving the resulting high-dimensional parameter spaces.

### B. PLATFORM DYNAMICS AND PHYSICAL CONTROLLABILITY

With the exception of [113], every design across Subsections III-B through III-F models the UAV as a point mass with unconstrained acceleration, ignoring roll-pitch-yaw dynamics, aerodynamic drag, propeller efficiency curves, and mechanical jitter induced by wind turbulence. As established in Subsection III-A, jitter is not a small perturbation: UAV pitch oscillations degrade AoA estimation more severely as the antenna array grows, which is precisely the operating regime that 6G massive antenna designs target. The 6-DoF trajectory analysis of [113] demonstrates that nominally optimal trajectories derived from kinematic point-mass models are often mechanically infeasible, and that incorporating physical controllability constraints changes the optimal trajectory qualitatively rather than marginally. Future designs must either embed control-aware trajectory constraints from the outset or formally certify that planned trajectories are aerodynamically achievable, particularly for high-mobility sensing scenarios such as target tracking and emergency response.

### C. SENSING METRIC SELECTION AND ITS ARCHITECTURAL CONSEQUENCES

Across Table 3 through Table 8, four distinct sensing metrics appear: beam-pattern gain, CRLB, sensing SNR,

and sensing rate. The choice of metric is not stylistic—it determines which system parameters become binding constraints and which algorithmic families are effective. As established in Subsection III-C, beam-pattern gain constraints yield tractable formulations suited to scenarios where target direction is known; CRLB constraints introduce a coupling between waveform parameters and trajectory that beam-pattern constraints miss; sensing rate and radar MI metrics are the most information-theoretically complete but also the most computationally demanding. Despite this, the vast majority of RIS-augmented ISAC designs—where the additional degrees of freedom make the metric choice most consequential—still use sensing SNR proxies rather than CRLB or radar MI. A systematic comparison of these metrics under unified channel and hardware assumptions, and particularly their interaction with RIS reconfigurability and UAV mobility, remains an important open problem.

### D. ALGORITHM DESIGN: BEYOND THE AO-DRL DICHOTOMY

The optimization landscape across all six subsections reveals a structural tension between two algorithmic families. AO with SCA provides convergence guarantees and strict constraint adherence but requires re-solving at each channel realization and converges to local optima whose quality degrades as the number of coupled variables grows. DRL and its multi-agent extensions generalize better across channel realizations and environment configurations but cannot guarantee constraint satisfaction at every time step and require large offline training datasets whose distribution may not match the deployment environment. Transfer-learning-enhanced DRL, as in [134], and meta-learning DRL, as in [167], reduce the training overhead substantially, but neither approach is robust to adversarial channel conditions, as demonstrated by [173]. LLM-based optimization, introduced in [141], offers strong zero-shot generalization but faces uncertain constraint adherence and interpretability challenges. Hybrid architectures—using AO for structural decomposition and DRL or LLMs for the hardest subproblems—represent an underexplored middle ground that could inherit the robustness of model-based methods and the generalization of learning-based methods simultaneously. Federated learning across UAV swarms further offers a path to distributed policy training without centralizing sensitive channel or positional data.

### E. IMPERFECT CSI AND ROBUSTNESS UNDER UNCERTAINTY

Perfect CSI availability for optimization is assumed by the majority of designs in every subsection. This assumption is most damaging in three specific contexts identified by the reviews. First, RIS-assisted channels are among the hardest to estimate accurately because the cascade BS-RIS-user channel has a product structure that requires dedicated pilot sequences; most RIS-ISAC designs ignore this overhead and treat RIS channel estimation as a solved problem. Second, eavesdropper CSI is almost never available to the

defending system in practice, yet the majority of security designs in Subsection III-F assume perfect adversary CSI. Third, target CSI in sensing—the radar cross-section statistics and precise position—is inherently uncertain because the target is uncooperative. Robust optimization frameworks that handle all three CSI uncertainties simultaneously—using bounded error models, probabilistic constraints, or distributionally robust formulations—have been applied only in isolated cases and never jointly. Extending the worst-case robust designs of [121] and [185] to scenarios combining RIS channel uncertainty, eavesdropper CSI imperfection, and sensing model mismatch represents a natural and high-impact research direction.

#### F. SECURITY: THREE DISTINCT THREAT CATEGORIES

Subsection III-F establishes that security threats in UAV-ISAC systems fall into three structurally distinct categories that require different countermeasures and have largely been addressed independently. *Communication secrecy threats*—eavesdropping and jamming—are the most extensively studied, with trajectory steering, RIS beamforming, and cooperative jamming UAVs as the primary countermeasures. *Sensing spoofing and deception attacks*—where adversaries inject false radar echoes, manipulate their radar cross-section, or physically obstruct sensing beams—have received almost no attention in the UAV-ISAC literature despite their practical importance in contested airspace and autonomous vehicle environments. *Cross-domain information leakage*—where communication symbols reveal sensing intent or vice versa, allowing an observer to infer target locations from intercepted communication waveforms—has not been formally bounded or modeled. The three categories interact: a system that defends against eavesdropping by null-steering may inadvertently reveal its sensing intent through the residual radiation pattern. Future security designs should address all three threat categories within a unified adversary model, rather than optimizing against only one while ignoring the others.

#### G. ENERGY-AOI-SECURITY CO-DESIGN

The reviews across Subsections III-D, III-E, and III-F reveal three important pairwise interactions that have not been jointly characterized. First, the energy-AoI trade-off: AoI-optimal designs in Subsection III-D require frequent short sensing visits, which incur high mobility energy costs, while energy-optimal designs prefer infrequent long sensing sessions, which inflate AoI. Realistic aerodynamic energy models—accounting for velocity-dependent propulsion, hover stability, and recharging strategies—have not been applied to AoI minimization despite being standard in EE research. Second, the security-AoI interaction: an adversary who jams the sensing link artificially inflates AoI, so delay-optimal and AoI-optimal designs that ignore jamming are structurally fragile. Reference [173] demonstrates that anti-jamming EE is achievable through game-theoretic DRL, but this framework has not been applied to the AoI metric. Third,

the energy-security trade-off: secure designs that require complex iterative beamforming updates consume more processing power, while energy-efficient designs that reduce update frequency may create exploitable periodic vulnerabilities. A unified framework that simultaneously minimizes AoI and energy consumption while maintaining security guarantees under adversarial channel conditions remains an important and largely unaddressed open problem.

#### H. MULTI-LAYER AND MULTI-HOP NETWORK INTEGRATION

UAV-ISAC systems in practical 6G deployments will not operate in isolation but must integrate with terrestrial networks, satellite backhaul, and MEC infrastructure. Several integration challenges remain open. The SAGIN framework of [172] shows that multi-layer Doppler environments require two-step-ahead EKF prediction for beam alignment, but does not address the backhaul latency that arises when satellite links introduce round-trip delays of tens of milliseconds. The MEC-ISAC frameworks of [168] and [171] demonstrate that computation scheduling—not transmit power—is the binding energy constraint in offloading systems, but neither addresses scalability to large UAV fleets where the MEC server becomes a bottleneck. Multi-hop UAV relay networks, where sensed data must traverse several UAV hops before reaching the ground station, introduce AoI dynamics not captured by single-hop models and create new interference management challenges not present in direct links. Hierarchical MEC frameworks that co-optimize offloading decisions, sensing schedules, and UAV trajectories across multiple network layers—while maintaining latency, energy, and security guarantees—represent a research challenge of practical urgency for 6G deployment.

#### I. STANDARDIZATION, SPECTRUM REGULATION, AND INTEROPERABILITY

As established in Section II, standardization efforts by 3GPP (Releases 18 and 19), ETSI's ISG-ISAC, IEEE 802.11bf, and ITU-R have begun to define sensing service KPIs and channel models for terrestrial ISAC. However, UAV-enabled ISAC has not yet received a dedicated standardization track, and several gaps between research designs and standardizable specifications remain. Most research designs assume centralized optimization with perfect knowledge of all system parameters, whereas standardized systems must operate with limited feedback, distributed control, and interoperability constraints across vendors. Spectrum sharing between UAV-ISAC waveforms and existing radar, aviation, and cellular allocations requires regulatory frameworks that do not yet exist for the sub-6 GHz and millimeter-wave bands most relevant to 6G. Privacy regulations—including GDPR-like requirements for data collected by airborne sensing platforms—impose constraints on how sensing data can be stored, shared, and processed that optimization frameworks universally ignore. Future research should develop UAV-ISAC designs that are explicitly compatible with emerging 3GPP Release-19 and 6G evaluation assumptions, including

the multi-TRP assisted UAV sensing frameworks and standardized channel models, to accelerate the transition from research contributions to deployable specifications.

### J. COST, SCALABILITY, AND ENVIRONMENTAL SUSTAINABILITY

Two systemic barriers to UAV-ISAC deployment that the optimization literature largely ignores are hardware cost and environmental impact. Current research assumes UAVs with high-gain antenna arrays, active RIS elements, onboard computing, and full-duplex radio front-ends—hardware configurations whose combined cost places them well beyond consumer-grade platforms. Lightweight, cost-effective UAV platforms with reduced antenna counts and simpler beam-forming architectures sacrifice some performance but enable wider deployment; designing ISAC systems that gracefully degrade under hardware constraints rather than failing outright is an open challenge. The environmental dimension—carbon footprint of propulsion, acoustic noise in urban deployments, and electromagnetic interference with wildlife—has received almost no attention in the technical literature despite growing regulatory pressure. Blockchain-based decentralized resource management, as noted in prior work [124], offers one path toward scalable fleet coordination without centralized infrastructure, but its latency and throughput characteristics under ISAC time constraints have not been evaluated. Renewable energy integration—solar panels on UAV surfaces, energy harvesting from ambient RF sources, and coordinated charging at multiple ground stations—represents a natural extension of the multi-charging-station trajectory designs of [165] that has not yet been combined with ISAC sensing and communication constraints.

### V. CONCLUSION

This survey has presented a systematic and multi-dimensional review of UAV-based ISAC systems, spanning CE and beam tracking, throughput maximization, WSR-sensing co-optimization, AoI minimization, EE enhancement, and PLS. Across these six domains, a coherent set of design principles has emerged: jitter modeling is a precondition for reliable CE; shadowing-dominated fading channels exert a decisive and underappreciated influence on system performance; sensing metric selection—whether beam-pattern gain, CRLB, SNR, or sensing rate—shapes the entire optimization architecture; and AO and DRL are complementary paradigms whose hybrid integration offers a promising but largely unexplored path forward. Security analysis further reveals that communication secrecy, sensing spoofing, and cross-domain leakage constitute structurally distinct threat categories, each demanding dedicated countermeasures within a unified adversary framework. Despite these advances, several challenges remain. Realistic aerodynamic platform models, composite fading channel assumptions, robust optimization under imperfect CSI, and joint energy-AoI-security co-design have received limited attention relative to their practical

importance. Closing these gaps—alongside the development of standardization frameworks compatible with 3GPP Release-19 and emerging 6G specifications—will be essential for transitioning UAV-ISAC from research prototype to deployed infrastructure. As UAVs evolve into intelligent, multi-functional aerial nodes capable of simultaneously sensing, communicating, and computing, their integration into 6G networks represents not merely an incremental advancement but a foundational shift in the architecture of future wireless systems.

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