

Research Project

Intelligent Decision-making for Cognitive ISAC Networks

The optimization of traditional cellular communication networks has been extensively studied to maximize data throughput, reduce interference, and achieve ubiquitous wireless coverage. With the emergence of integrated sensing and communication (ISAC) as a key enabling technology for 5G-Advanced (5G-A) and sixth-generation (6G) wireless systems, next-generation networks are expected to evolve toward dual-functional platforms [1]. While most existing ISAC works primarily focus on classical closed-loop radar-based sensing [1], future ISAC networks are shifting toward cognitive radars [2] that intelligently adapt to the dynamic surrounding environment (e.g., user locations, target activities, varying blockages, and dynamic radio maps).

To this end, cognitive radars employ a perception-action cycle that continuously adapts transmission strategies, beamforming policies, resource allocation, and coverage patterns according to the surrounding environment. Interesting application examples include automotive systems such as vehicle-to-everything, telemedicine, 6G wireless networks, and Industry 5.0 as illustrated in Figure 1. While a limited number of works have investigated the optimization of cognitive ISAC single-node systems [3], the optimization of cognitive ISAC networks remains largely underexplored.

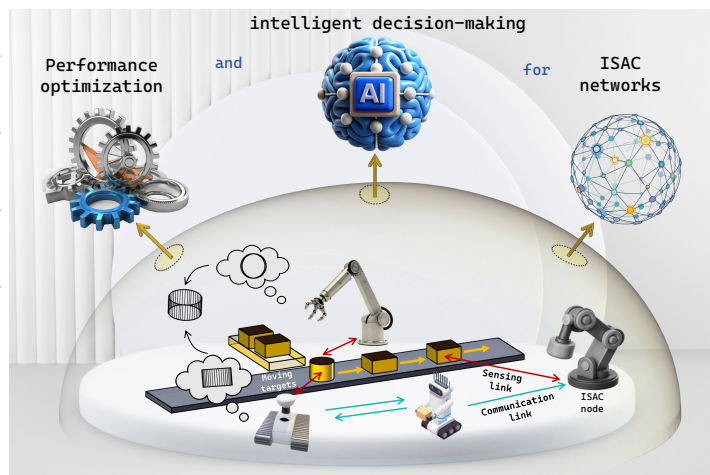


Figure 1: Illustration of a cognitive ISAC network operating in an Industry 5.0 scenario, highlighting the interaction between communication and sensing within a dynamic environment.

Building on this motivation, this project aims to investigate the **design of novel and intelligent optimization frameworks** for **cognitive ISAC networks** that address the following optimization problems (among others):

P1: Adaptive Coverage

While seamless coverage has been one of the primary objectives of traditional wireless communication networks, the coverage problem in ISAC systems is fundamentally different. In particular, although dense wireless network deployments generally increase interference and may degrade the communication performance, the sensing functionality can partially benefit from such interference, as it enables advanced multistatic radar processing. In this context, the optimization of ISAC network coverage has been studied in the context of 5G-A and 6G systems in [4]. The authors in [5] investigated base station deployment strategies based on the area Cramér–Rao bound, while the authors in [6] employed stochastic geometry to analyze the coverage and the ergodic rate of ISAC networks. Nevertheless, this project focuses on cognitive ISAC networks, where coverage is expected to intelligently adapt to the dynamic environment. For instance, on-demand coverage for hotspot areas, intelligent multistatic coverage for moving targets, and adaptive deployment strategies tailored to time-varying scenarios need to be addressed.

P2: Interference Mitigation

Xu *et al.* in [7] identified interference management as one of the most critical challenges in ISAC networks, with interference originating from multiple sources such as self-interference,

mutual coupling, crosstalk, clutter, and multi-user interference. The associated optimization problems for different interference types were discussed in [7], while mitigation techniques for inter-vehicle communications and Beyond 5G/6G networks were investigated in [8] and [9], respectively. A comprehensive survey on interference management for ISAC networks can be found in [10]. Nevertheless, interference mitigation in cognitive ISAC networks remains significantly more challenging due to the dynamic nature of the environment. For example, while most existing works assume static clutter models, practical clutter models are geometry-dependent and highly time-varying, requiring more advanced and adaptive suppression techniques.

P3: Resource Allocation

Resource allocation in networked ISAC systems aims at efficiently distributing communication, sensing, and computational resources to maximize the overall network performance. This includes, for instance, the scheduling of sensing and communication functions over orthogonal or overlapping resources across time, frequency, space, and code domains [11]. Resource allocation problems for ISAC networks have been studied in various contexts, including green unmanned aerial vehicle (UAV)-based networks [12], target tracking [13], and 6G vehicle-to-everything (V2X) systems [14]. Nevertheless, resource allocation in cognitive ISAC networks is more challenging due to the variability of the environment, requiring environment-aware and predictive decision-making to dynamically allocate the available network resources.

The guidelines for this project can be summarized as follows:

- Conduct a targeted literature review on ISAC networks [1], cognitive radars [2], reinforcement learning [15], and mathematical optimization methods [16].
- Select and investigate **at least one** of the above-mentioned optimization problems (**P1-P3**).
- Develop and implement an online optimization framework for the considered problem.
- Evaluate and compare the proposed solution against well-known benchmark schemes.

PREREQUISITES

Scientific skills	Interest in communication and sensing. Basic knowledge of convex optimization and reinforcement learning.
Programming skills	Experience in Python programming.
Language skills	English fluency

SUPERVISOR	Dr.-Ing. Amine Lahmeri {amine.lahmeri}@fau.de
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Start date:	TBD
End date:	TBD

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