Dynamic Spectrum Sharing via Stochastic Optimization

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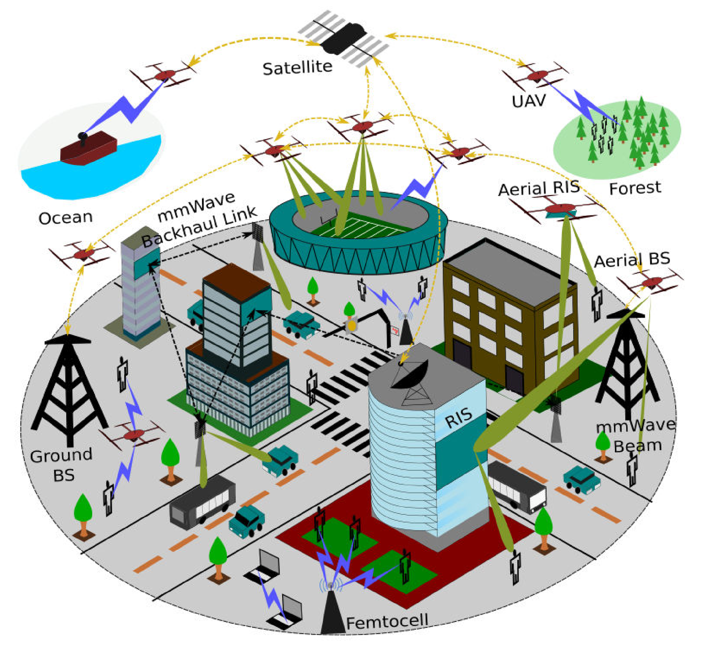
1. Overview

Challenges: General mathematical framework to integrate new technologies, e.g. UAVs and RIS, and utilize the new degrees of freedom for resilient coexistence of communication and radar over shared spectrum.
Observation: Avoiding interference between users at all times is too conservative in the wake of increasing demand for throughput and dual communication and sensing functionality.
Solutions: A new paradigm in which we move from hard deterministic constraints to stochastic schemes with desired low probability of harmful interference. Developing a stochastic optimization framework for resilient spectrum sharing in a communication network that includes new technologies like RIS and UAV. Extending the framework to include coexistence of communication and radar.



2. UAV Corridors in Cellular Networks

Goal: Optimize the average SINR across both UAVs and terrestrial ground-users.
Performance Function:

$$\Phi_{\text{MP}}(\boldsymbol{V},\boldsymbol{\Theta},\boldsymbol{\rho}) = \sum_{n=1}^{N}\int_{V_n}\gamma_{\text{MP}}^{(n)}(\boldsymbol{q};\boldsymbol{\Theta},\boldsymbol{\rho})\lambda(\boldsymbol{q})d\boldsymbol{q},$$
$$\text{s.t. } \rho_n \le \rho_{\max} \qquad \forall n \in \{1,\cdots,N\},$$

where ρ_n is the BS n's transmission power and

$$\gamma_{\text{MP}}^{(n)}(\boldsymbol{q};\boldsymbol{\Theta},\boldsymbol{\rho}) = -\log\left[\mu + \frac{1}{(\mathtt{SINR}_{\mathtt{lin}}^{(\mathtt{n})}(\boldsymbol{q};\boldsymbol{\Theta},\boldsymbol{\rho})+\nu)}\right].$$

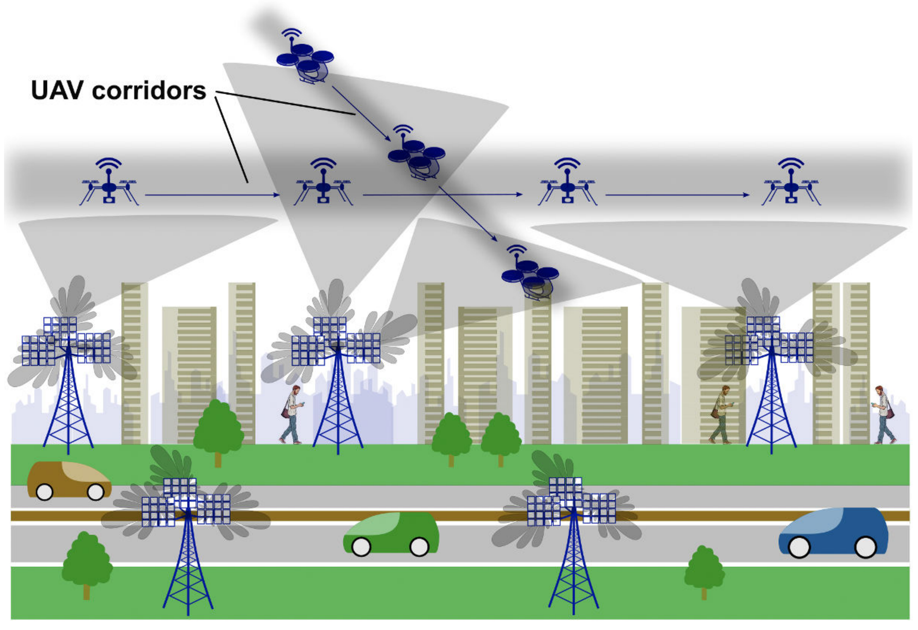


Figure: Illustration of a cellular network with downtilted and uptilted BSs providing coverage to ground users as well as UAVs flying along corridors (blurred gray).

S. Karimi-Bidhendi, G. Geraci, and H. Jafarkhani, "Optimizing Cellular Networks for UAV Corridors via Quantization Theory," Revision submitted, Apr. 2024.

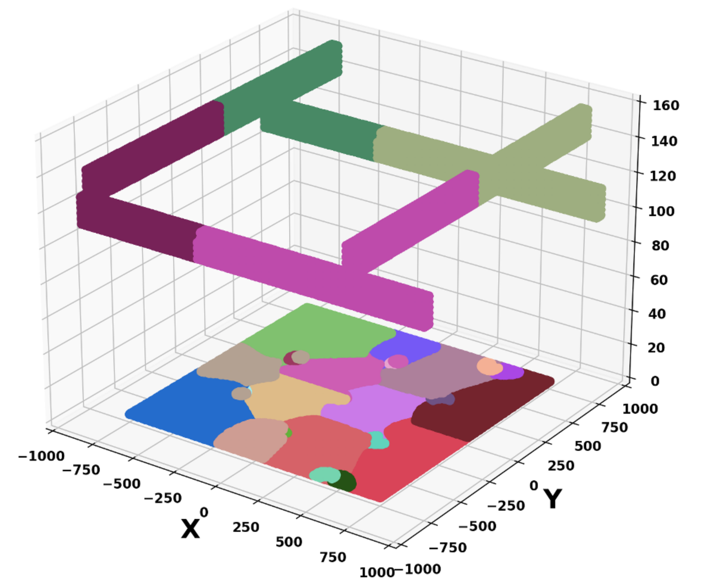


Figure: Optimized cell partitioning of GUEs and UAVs ($\mu = \nu = 0.1$).

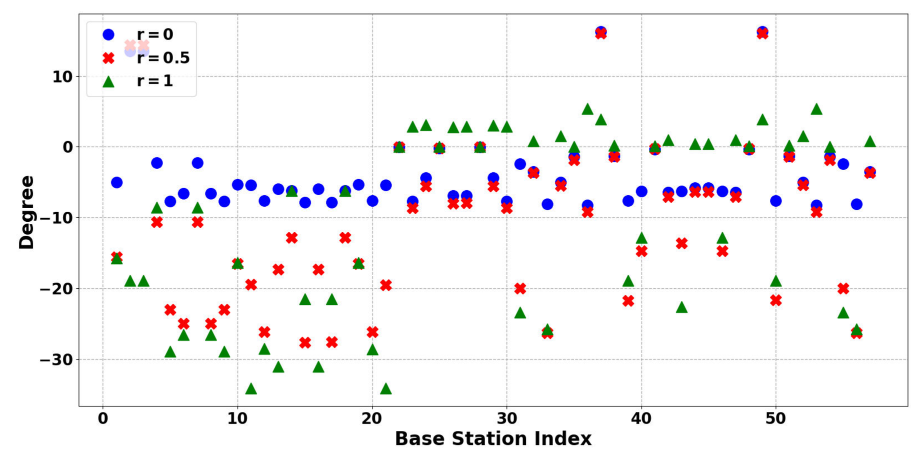


Figure: Optimized vertical tilts θ_i^* for: GUEs only ($\alpha = 1$, green triangle), UAVs only ($\alpha = 0$, blue circle), and both ($\alpha = 0.5$, red cross).

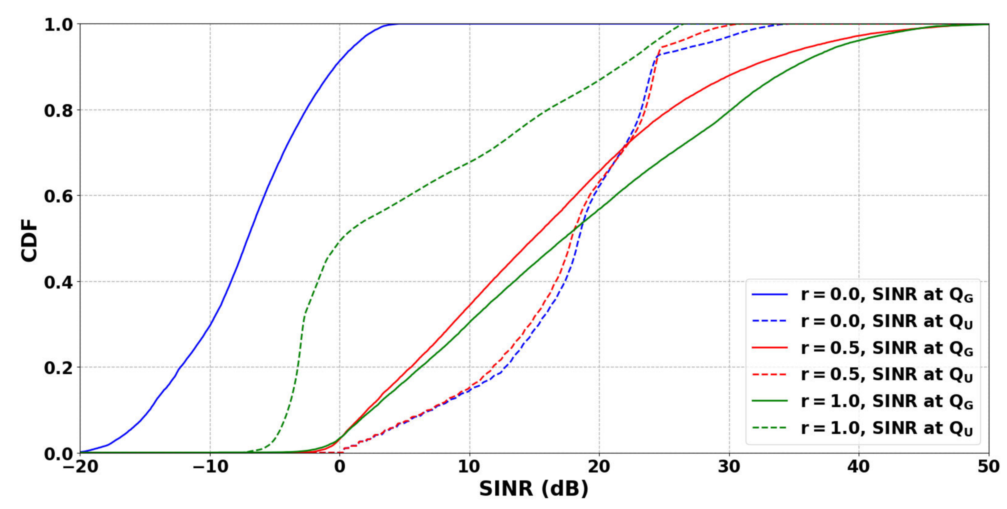


Figure: CDF of the SINR (dBm) at UAVs (dash-dash) and GUEs (solid) when the network is optimized for GUEs only ($\alpha = 1$), UAVs only ($\alpha = 0$), and both ($\alpha = 0.5$).

3. Dual-Functional Radar-Communication Beamforming with Outage Probability Constraints

System Model: K single-antenna users, a base station with N antennas, and imperfect channel state information: $\mathbf{C}_k = \mathbb{E}[\mathbf{h}_k\mathbf{h}_k^H] = \hat{\mathbf{C}}_k + \mathbf{E}_k$
Objective Function: We aim to find K beamformers for minimizing the mean square error of the achieved and the ideal sensing beampattern:

$$L(\mathbf{R},\alpha) = \frac{1}{L}\sum_{l=1}^{L}\left[\alpha\phi(\theta_l) - \mathbf{a}^H(\theta_l)\mathbf{R}\mathbf{a}(\theta_l)\right]^2,$$

with the equal per antenna power constraint and a probability of outage constraint for each user:

$$[\mathbf{R}]_{n,n} = \frac{P_T}{N}, \quad \forall n \in \{1,\ldots,N\},$$
$$\Pr[\text{SINR}_k \ge \gamma_k] \ge 1 - p_k \quad \forall k \in \{1,\ldots,K\},$$

where L is the number of grids, $\phi(\theta)$ is the desired beampattern at angle θ, α is a scaling factor, $\mathbf{a}(\theta)$ is the steering vector, and $\mathbf{R}$ is the transmit waveform covariance.
Solution: Write the probabilistic constraints in terms of the error function and solve a semidefinite programming (SDP) with a penalty term that ensures rank-1 solutions.

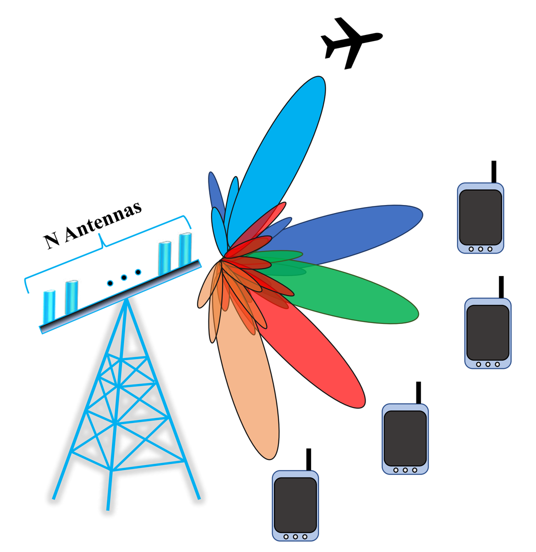


Figure: A DFRC system with K downlink communication users and a radar directions of interest

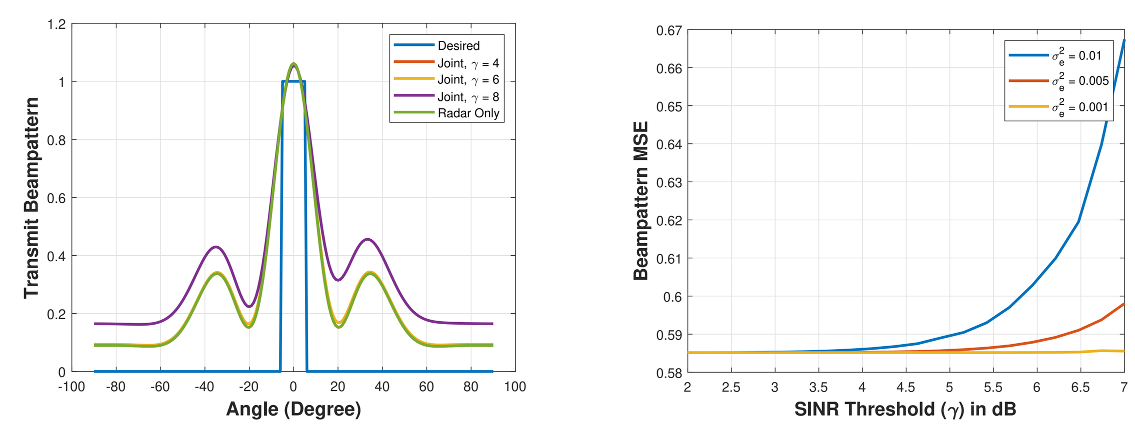


Figure: 100 Monte Carlo simulations of (Left) Beampattern for 2 users, $N = 5$ antennas, $p_k = 0.02$, and different values of SINR threshold; (Right) Beampattern MSE for $p_k = 0.001$ and different values of error in channel estimation

4. Stochastic Optimizations and Approximate Solutions

Dynamic spectrum allocation: Optimally choose a string (sequence) of spectrum allocation policies to maximize a desired spectrum usage utility function over time. The problem can be transformed as a *string-optimization problem:*

$$\text{maximize } f(S)$$
$$\text{subject to } S \in \mathbb{T}$$

where f is the utility function that we wish to maximize (e.g., expected throughput or negative expected latency), $\mathbb{T}$ is the set of all permissible strings of spectrum allocation policies over time horizon of K allocation steps. An element of $\mathbb{T}$ is a sequence of policies.

A *policy* is a posterior density over the action space (permissible spectrum allocations) given the current state of the network (current allocations and (probabilistic) interference constraints).

Greedy strategy: Determining the optimal string of policies becomes computationally intractable with increasing size of state/action space and optimization horizon. Therefore, we often have to resort to approximate solutions. The most common approximation scheme is the *greedy strategy,* in which we sequentially select the policy that maximizes the increment in the utility function at each step. But how good is the greedy scheme relative to the optimal scheme?

Performance bound: We have derived a *ratio bound* for the performance of greedy scheme relative to the optional scheme. The bound guarantees that the greedy scheme achieves at least a factor of β of the optimal scheme.

$$\frac{f(G_K)}{f(O_K)} \ge \beta, \text{ with } \beta = \frac{f(G_K)}{\sum_{k=1}^{K}\max_{s\in\mathbb{S}(G_{k-1})} f(s)}.$$

B. Van Over, B. Li, E. K. P. Chong, and A. Pezeshki, "On Bounds for Greedy Schemes in String Optimization based on Greedy Curvatures," *submitted to IEEE CDC 2024*, Mar. 2024 (invited paper).

Derivation of the bound *does not require submodularity* of f and β is easily computable.

5. Outreach Activity

Mini-symposium on Data-Driven Optimization of Spectrum Sharing Networks, held at Duke University in October 2023. The program included 11 technical talks, by speakers from NSF, Duke University, UC-Irvine, Colorado State University, Virginia Tech, Johns Hopkins, and ISL Inc.