WWRF Plenary

Towards 3D* Wireless Networks

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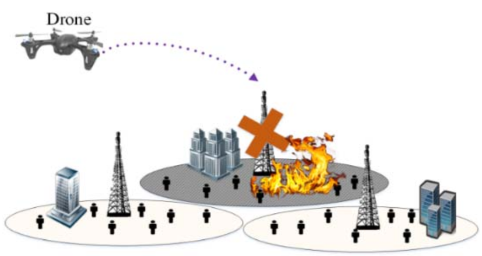
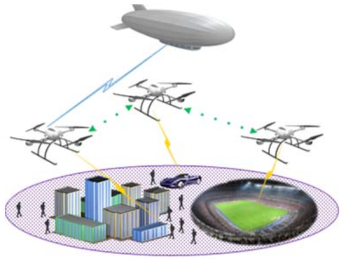
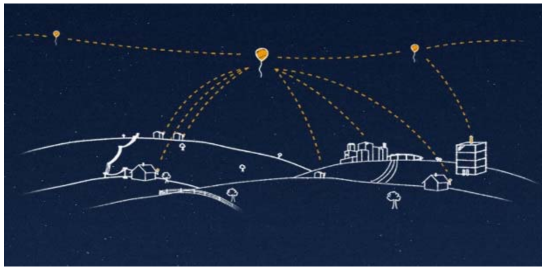
*** A small part of the talk may violate the 3D angle**

Drones as Flying Base Stations

- Drone base stations for emergency situations or hotspots
- Can bring high capacity in temporary events: Olympic games
  - Project examples: Ericsson and Qualcomm, AT&T, and ABSOLUTE







Global connectivity

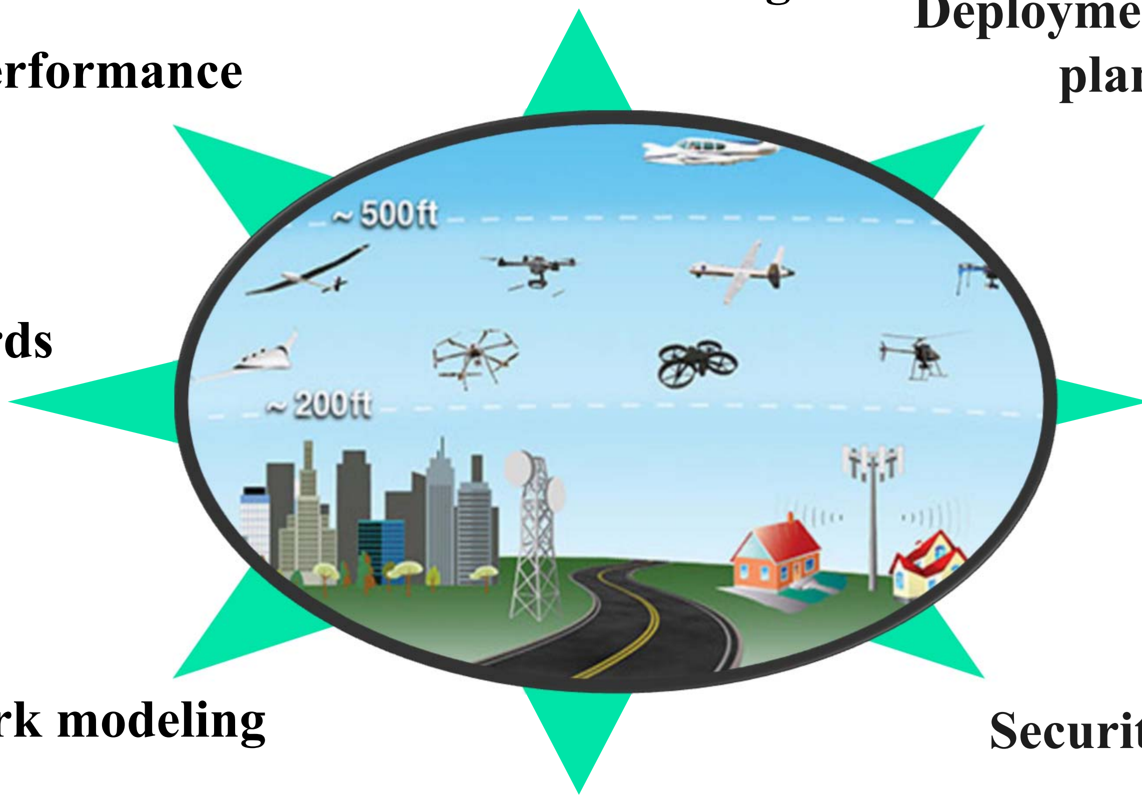
- Advantages
  - Adjustable altitude
  - On-demand connectivity
  - Low infrastructure low cost
  - Low altitude vs high altitude

Nokia's Drone base stations

Drones as Wireless Users

- Drones will require connectivity to enable applications such as delivery, rescue missions, and flying cars

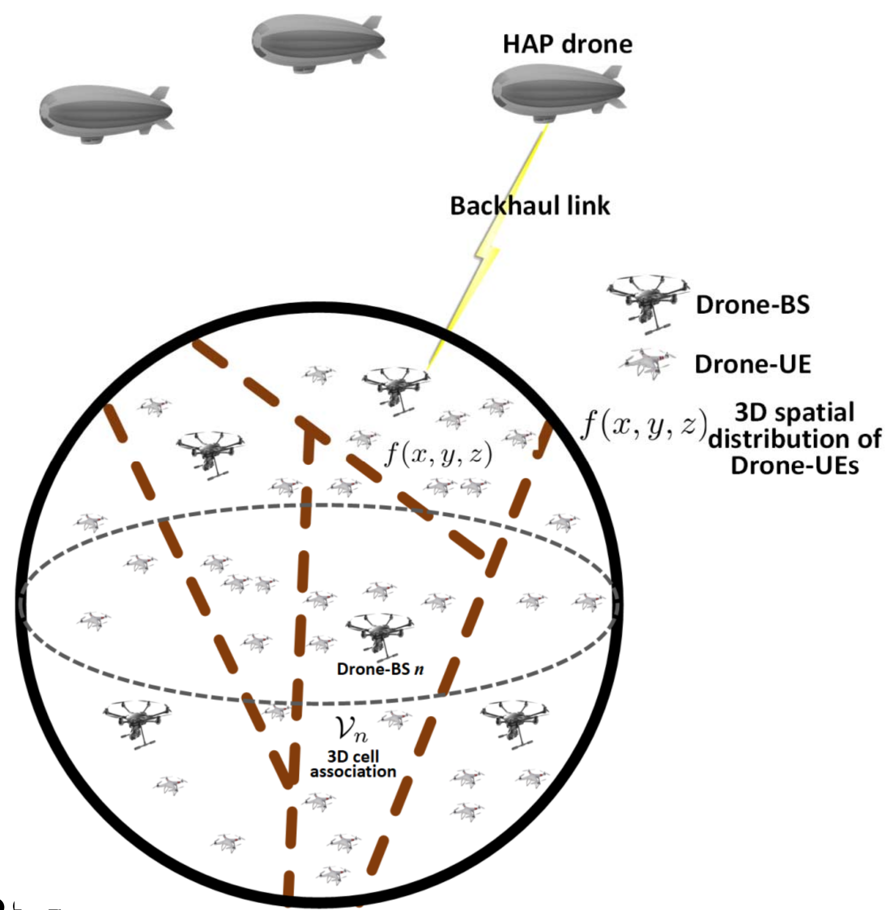
Challenges



- Let’s pose a more fundamental question: Can we build fully-fledged **standalone 3D** wireless networks with drones?

System Model

- **3D aerial network:**
  - Drone-users (drone-UEs)
  - Drone base stations (drone-BSs)
  - HAP drones for wireless backhaul



- **Important metrics:**
  - Connectivity
  - Latency

- **Two key problems:**
  - 3D **network planning** of drone-BSs
    - Deployment and frequency planning
  - 3D **cell association** for drone-UEs

Proposed Framework

3D deployment of drone-BSs and frequency planning: truncated octahedron cells

Drone-BSs' locations and co-channel cells

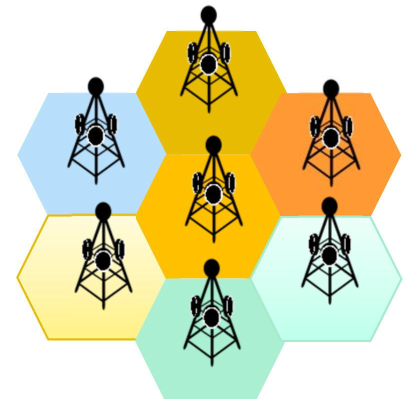
Optimal 3D cell association for minimum latency of drone-UEs using optimal transport theory

Estimating the spatial distribution of drone-UEs using machine learning tools

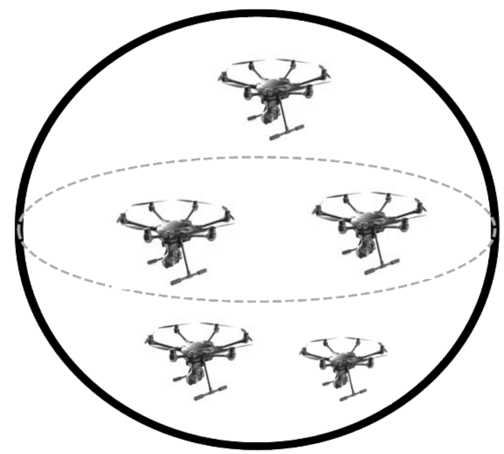
3D spatial distribution of drone-UEs

Network Planning of Drone-BSs

- Inspired by 2D hexagonal cells
  - Hexagons covers an area without gap or overlap
  - Closest to circle
    - Omni-directional antenna



- How about in 3D?
    - More dimensions (3D, more adjacent cells, etc.)

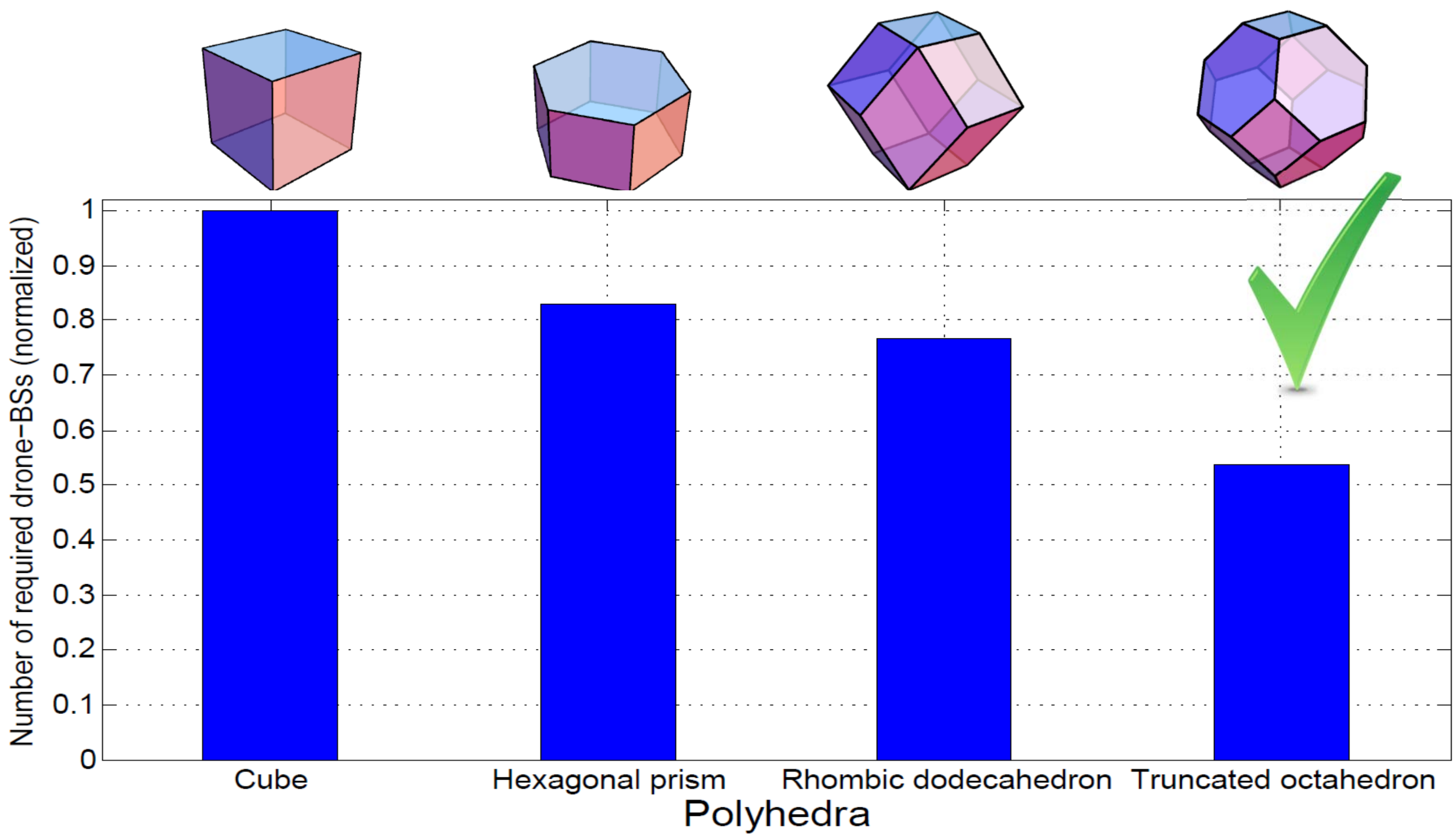


Criteria:

- Full coverage with minimum number of drones
- Closest shape to a sphere
- Tractable
- Candidates for regular 3D shapes: Cube, Hexagonal prism, Rhombic dodecahedron, Truncated octahedron

Results: Network Planning

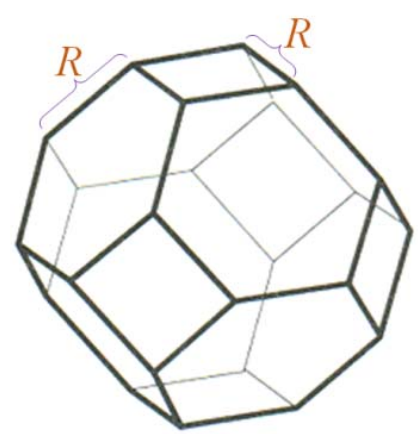
- Number of drone-BSs needed for full coverage of space
- Different **space filling polyhedra**



3D Network Planning of Drone-BSs

- **Truncated octahedron** structure will provide an initial way to place drone-BSs
- Placing drone-BSs at centers of truncated octahedrons

14 faces:
8 hexagons
6 squares



Deployment and Frequency Planning

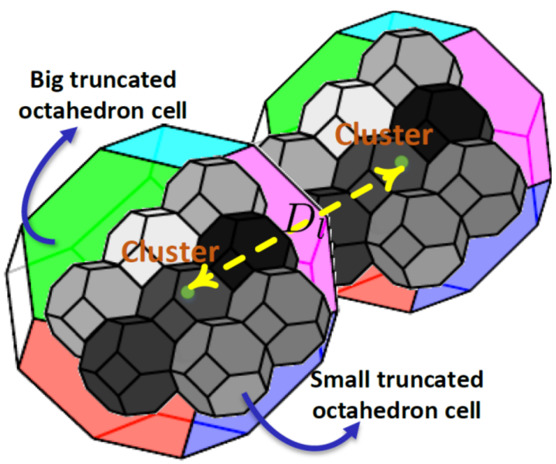
- **Theorem 1.** the three-dimensional locations of drone-BSs are:

$$\boldsymbol{P}_{\{a,b,c\}} = \left[x_o, y_o, z_o\right] + \sqrt{2}R\left[a+b-c, -a+b+c, a-b+c\right]$$

where *a, b, c* are integers chosen from set {…,-2,-1, 0, 1, 2,…}

- **Theorem 2.** the feasible integer frequency reuse factors can be determined by:

$$\begin{cases} q = \sqrt{\dfrac{\left[3(n_1^2+n_2^2+n_3^2)-2(n_1n_2+n_1n_3+n_2n_3)\right]^3}{27}}, \\ q = \sqrt{\dfrac{\left[3(m_1^2+m_2^2+m_3^2)-2(m_1m_2+m_1m_3+m_2m_3)\right]^3}{64}}, \end{cases}$$



n_1, n_2, n_3, m_1, m_2, and m_3 are integers that satisfy above equations

Integer frequency reuse factors: 1, 8, 27,64, 125…

vs 2D case: 1, 3, 4, 7, 9, 12,…

Latency-Minimal 3D Cell Association

- Latency in serving drone-UEs
  - Transmission latency
  - Backhaul latency
  - Computational latency

Depend on: resources, congestion, and 3D cell association

$$\min_{\mathcal{V}_n,\, n\in\mathcal{N}} \sum_{n=1}^{N}\left[\int_{\mathcal{V}_n} \frac{\beta K_n}{\underbrace{B_n \log_2\left(1+\gamma_n(x,y,z)\right)}_{\text{Transmission data rate}}} \underbrace{f(x,y,z)}_{\text{Drone-UEs' distribution}}\mathrm{d}x\mathrm{d}y\mathrm{d}z + \underbrace{\frac{\beta K_n}{C_n}}_{\text{Backhaul}} + \underbrace{g_n(\beta K_n)}_{\text{Computation}}\right],$$

$$K_n = L\int_{\mathcal{V}_n} f(x,y,z)\mathrm{d}x\mathrm{d}y\mathrm{d}z,$$

Average number of independent drone-UEs in cell *n*: K_n

Total number of drone-UEs (assumed to be large): L

3D cell partition: $\mathcal{V}_n$

β : Packet length

B_n : Bandwidth

Challenging to solve

Latency-Minimal 3D Cell Association

- Another representation of the problem:

$$\min_{\mathcal{V}_1,\ldots,\mathcal{V}_N} \sum_{n=1}^{N} \int_{\mathcal{V}_n} c(\boldsymbol{v}, \boldsymbol{s}_n) f(\boldsymbol{v}) \mathrm{d}\boldsymbol{v},$$

$$\text{s.t.} \quad \int_{\mathcal{V}_n} f(\boldsymbol{v}) \mathrm{d}\boldsymbol{v} = \frac{K_n}{L},$$

$$\mathcal{V}_l \cap \mathcal{V}_m = \emptyset, \ \ \forall l \neq m \in \mathcal{N}, \ \ \bigcup_{n \in \mathcal{N}} \mathcal{V}_n = \mathcal{V},$$

Location of drone-BS n

$$\boldsymbol{v} = (x, y, z)$$

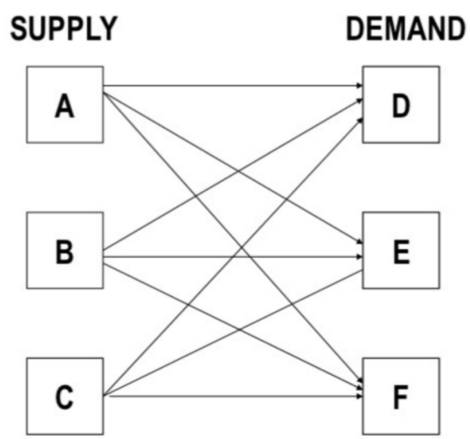
Location of arbitrary drone-UE

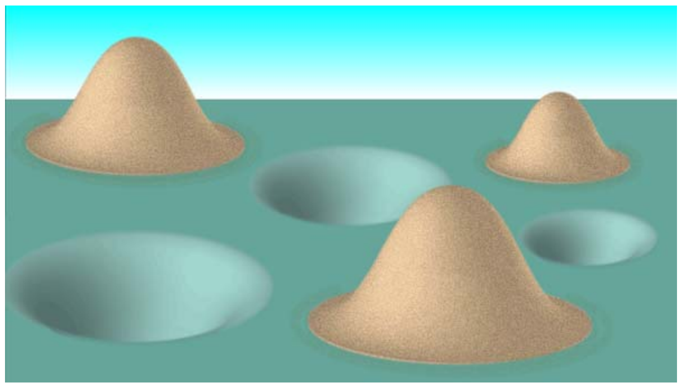
$$c(\boldsymbol{v}, \boldsymbol{s}_n) = \frac{\beta K_n}{B_n \log_2\left(1+\gamma_n(x,y,z)\right)} + \frac{L}{K_n}\left(\frac{\beta K_n}{C_n} + g_n(\beta K_n)\right)$$

- 3D cell partitions:
  - How to assign drone-UEs to drone-BSs in a continuous 3D space?
  - We need to go back 300 years…

Approach: Optimal Transport Theory

- Moving items from a source to destination with minimum cost





- What is the best way to move piles of sand to fill up given holes of the same total volume?
- **Goal:** Minimizing total transportation costs
- Where should each pile be moved?
- ***Our problem: transportation from drone-BSs to drone-UEs!***

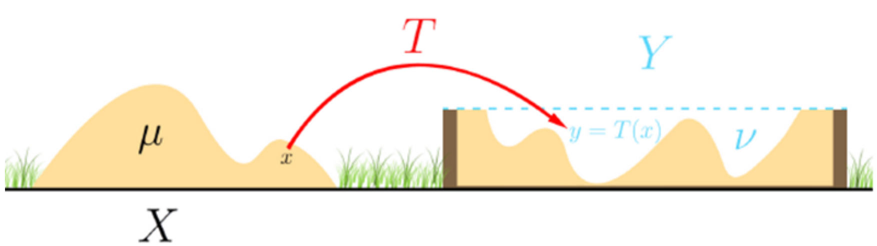
Monge-Kantorovich Transport Problem

- Given two probability distributions $\mu,\ v$

  μ: initial distribution
  v: final disribution
  Can be discrete or continuous

- Same amount of mass in source and destination
- What is the optimal mapping between μ and v ?

$$T : x \rightarrow y$$
$$y = T(x)$$



$c(x, y)$: transportation cost of moving x to y

$$\inf_T \int_X c(x, T(x))\mu(x)\mathrm{d}x$$

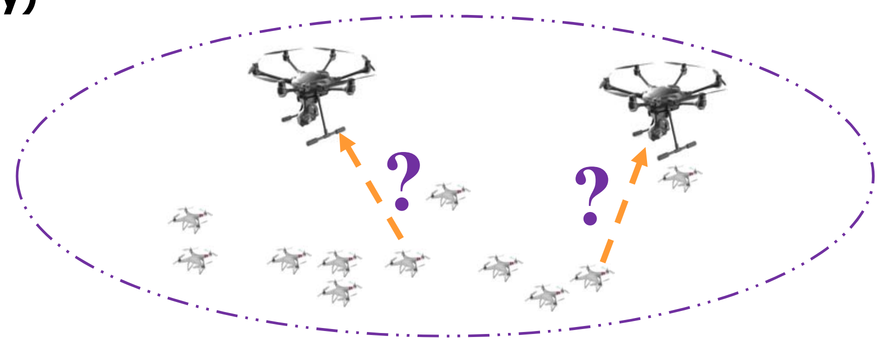
Solution Characterization

- Using tools from optimal transport theory
  - Finds optimal mapping between two probability measures
  - Considering a semi-discrete optimal transport problem
    - Mapping drone-UEs' distribution (continuous) to drone-BSs (discrete)
    - Optimal 3D cell partitions are related to optimal transport maps

Cost function (i.e., latency)

$$\min_{T} \int_{\mathcal{V}} c(\boldsymbol{v}, \boldsymbol{s}) f(\boldsymbol{v}) \mathrm{d}\boldsymbol{v}, \ \ \boldsymbol{s} = T(\boldsymbol{v}),$$

$$\left\{ T(\boldsymbol{v}) = \sum_{n=1}^{N} \boldsymbol{s}_n \mathbb{1}_{\mathcal{V}_n}(\boldsymbol{v}); \int_{\mathcal{V}_n} f(\boldsymbol{v}) \mathrm{d}\boldsymbol{v} = \frac{K_n}{L} \right\}$$



- T determines which drone-BS associated with which 3D point
- Optimal solution characterized given existence of an OT map

Solution Characterization

Theorem 3: the optimal 3D cell partitions are characterized by:

$$\mathcal{V}_l^* = \Big\{(x,y,z)\Big|\alpha_l + \frac{K_l}{L}h_l(x,y,z) + \frac{\beta}{C_l} + g_l'(\beta K_l) \leq \alpha_m + \frac{K_m}{L}h_m(x,y,z) + \frac{\beta}{C_m} + g_m'(\beta K_m),\ \forall l \neq m\Big\},$$

$$\alpha_l \triangleq \int_{\mathcal{V}_l} h_l(x,y,x) f(x,y,z)\mathrm{d}x\mathrm{d}y\mathrm{d}z \qquad h_l(x,y,z) \triangleq \frac{\beta}{B_l \log_2\left(1+\gamma_l(x,y,z)\right)}$$

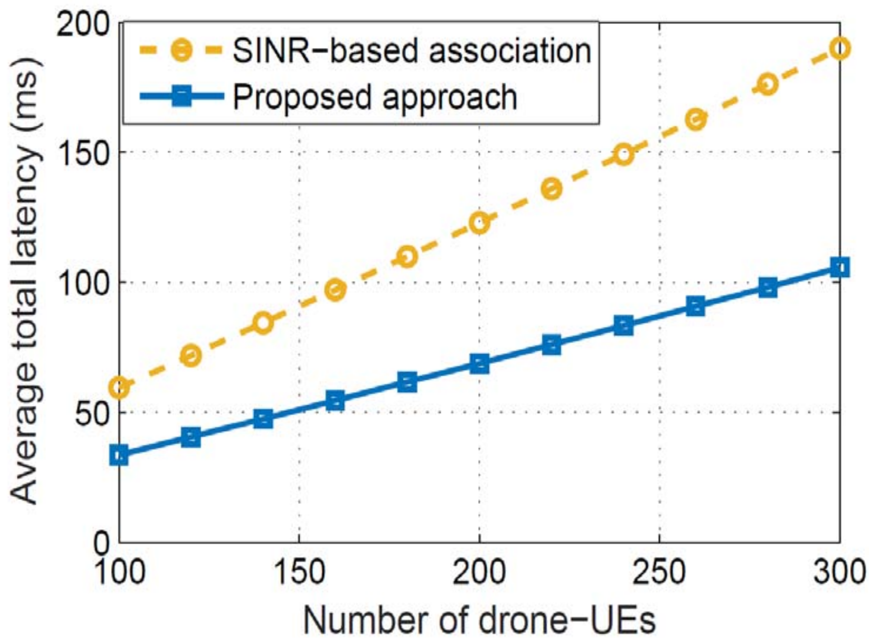
$$g_l{}'(K_l) = \left.\frac{dg_l(z)}{dz}\right|_{z=K_l}$$

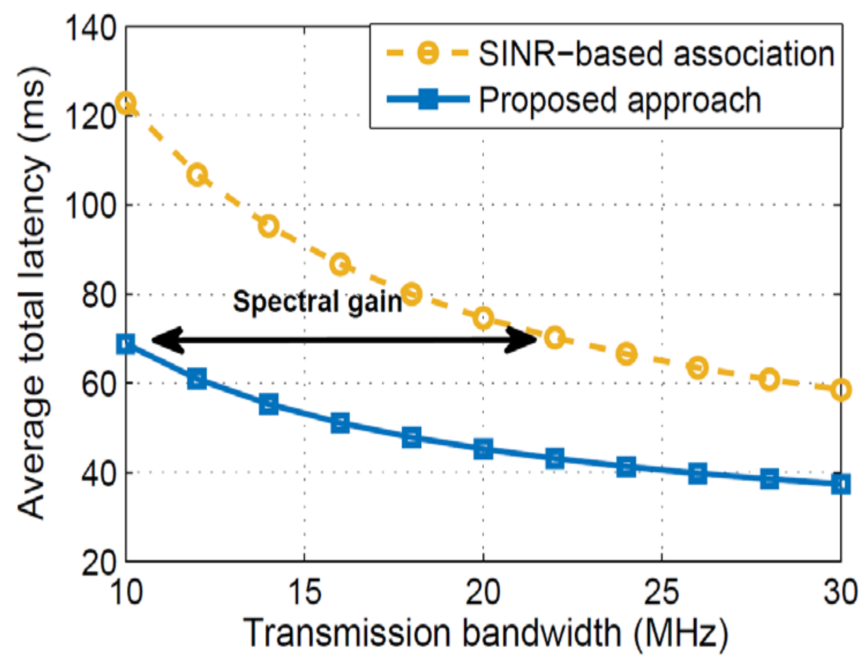
Note: 3D cell shapes depend on:

- Drone-UEs' distribution, drone-BSs' locations, backhaul rate, computational speed

Results: 3D Cell Association

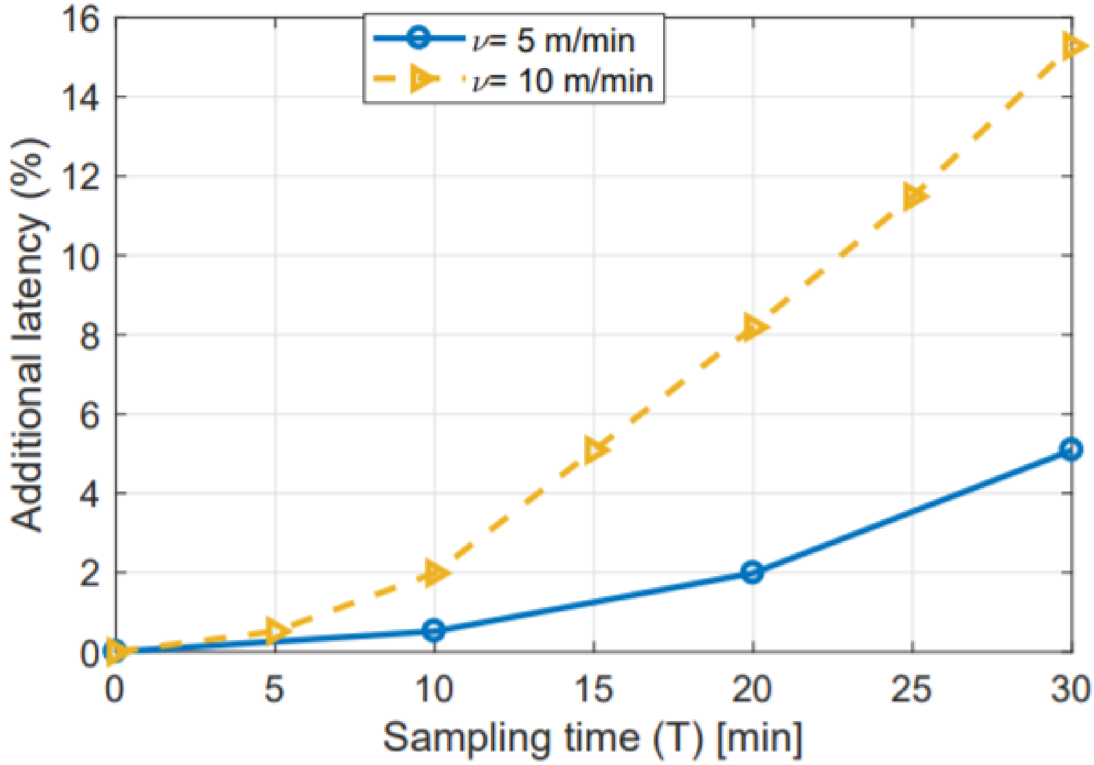
- Proposed approach vs. SINR-based association
  - Reduces latency
  - Improves spectral efficiency





Results: Accuracy-Optimality

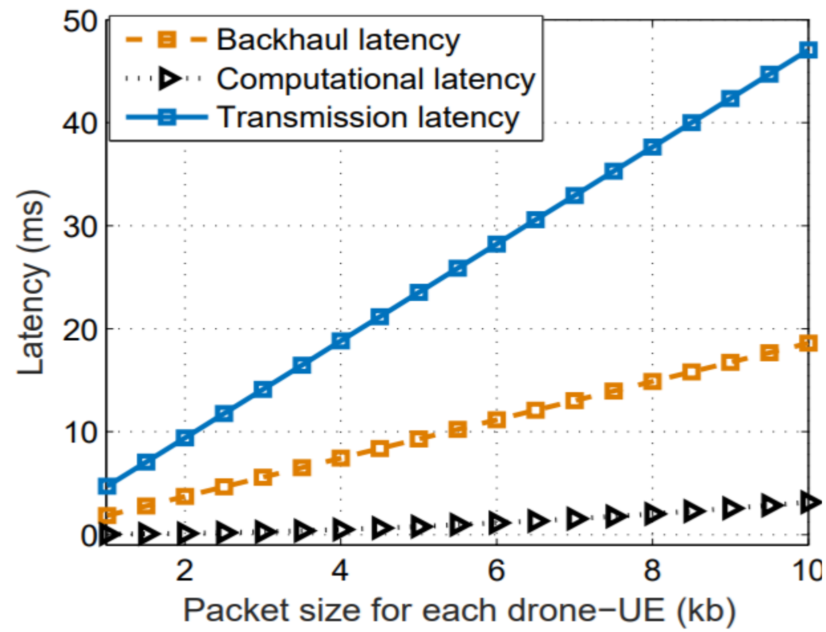
- There is a natural tradeoff between accuracy of machine learning estimation and optimality of cell association



- Smaller period of estimation better accuracy, less deviation from optimality but more overhead for estimation

Results: Latency

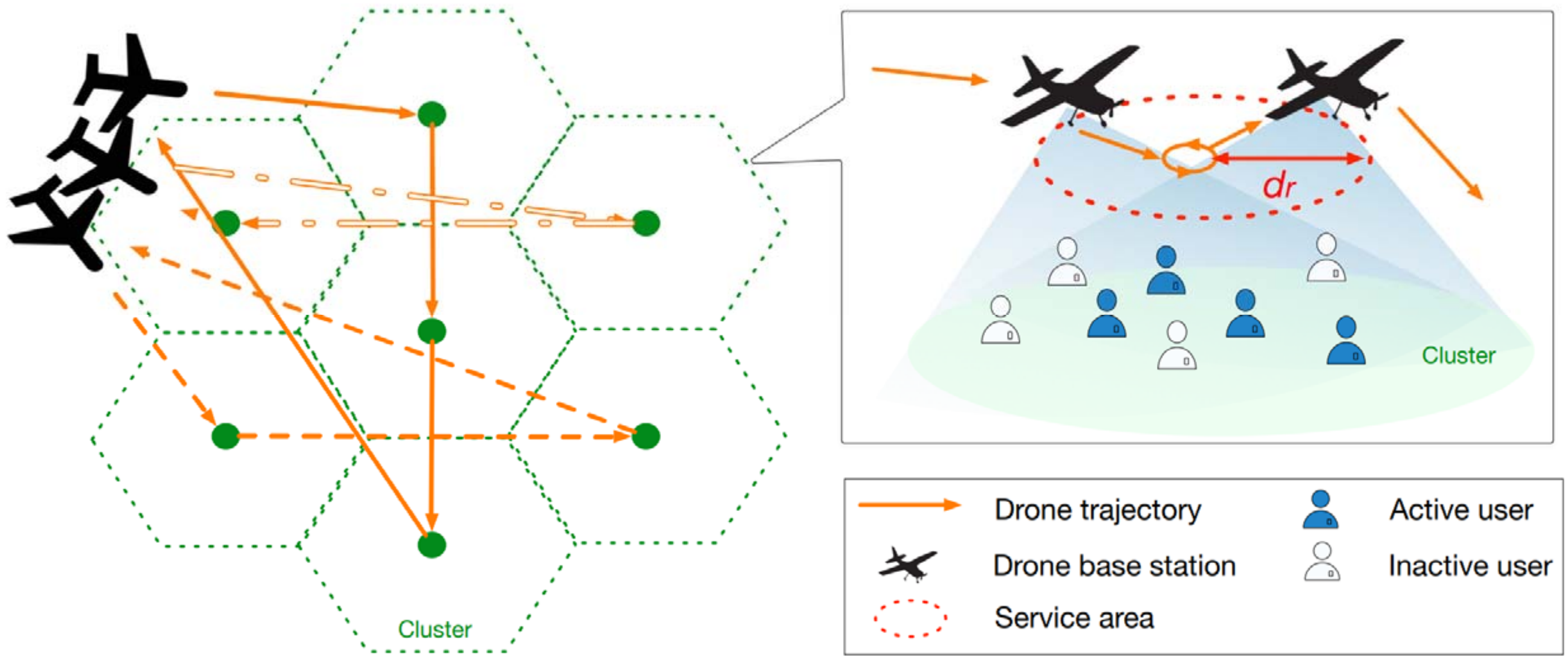
- Latency increases by increasing packet size
  - Transmission
  - Computation
  - Backhaul



- M. Mozaffari, A. Taleb Zadeh Kasgari, Walid Saad, Mehdi Bennis, Merouane Debbah, "Beyond 5G with UAVs: Foundations of a 3D Wireless Cellular Network", *IEEE Trans. on Wireless Communications*, vol. 18, no. 1, pp. 357–372, January 2019.

- What if we want to look at the actual movement of the drones?
  - Design of the trajectory becomes more complex than what is done in the traditional control literature (will look at 2D)
  - A key role for learning, let's see an example

System Model



- N fixed-wing drone base stations (DBSs) serving uplink users whose activity and transmission patterns are unknown
- How can we design the trajectories of the drones in a coordinated way while also taking into account unknowns?

Formal Problem Statement

- Formally a coverage maximization team game

$$\max_{\boldsymbol{\pi}} \overline{G}(\boldsymbol{\pi}) = \sum_{\boldsymbol{\xi}\in\mathcal{E}} G(\boldsymbol{\xi}) \prod_{n=1}^{N}\prod_{k=1}^{K} \pi_n(\xi\,|\xi_{n,k}, \tau_{n,k})$$

Successful service rate (team utility)

$$\text{s. t.} \quad \sum\nolimits_{\boldsymbol{\xi}\in\mathcal{E}} \prod_{n=1}^{N}\prod_{k=1}^{K} \pi_n(\xi\,|\xi_{n,k}, \tau_{n,k}) = 1,$$

$$\sum\nolimits_{a_{n,k}\in\mathcal{C}\cup\{O\}} \pi_n(\xi\,|\xi_{n,k}, \tau_{n,k}) = 1, \forall n\in\mathcal{N}, \boldsymbol{\xi}\in\mathcal{E}, k\in\mathcal{K},$$

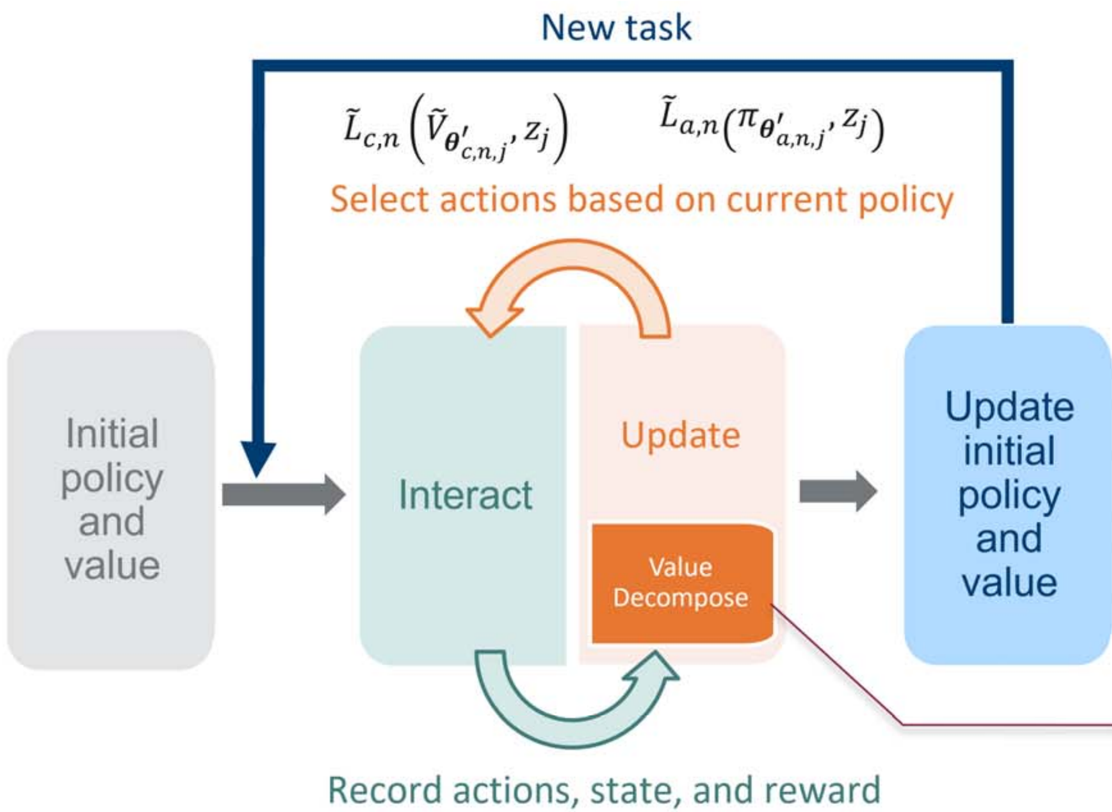
$$0 \leq \pi_n(\xi\,|\xi_{n,k}, \tau_{n,k}) \leq 1, \forall n\in\mathcal{N}, \boldsymbol{\xi}\in\mathcal{E}, k\in\mathcal{K},$$

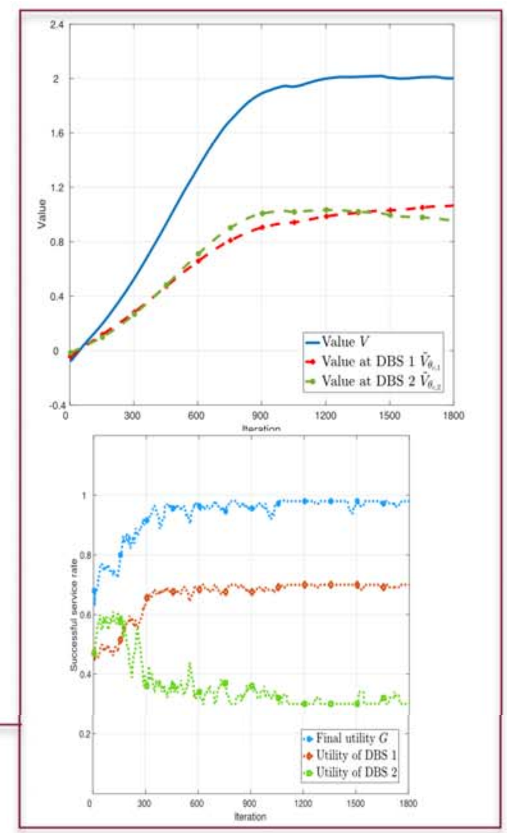
Trajectory And feasibility constraints

- The problem is non-convex with unknown environments
- Reinforcement learning is a natural solution but..
  - Scalability is needed for cooperation between drones
  - We need to build “cumulative knowledge”

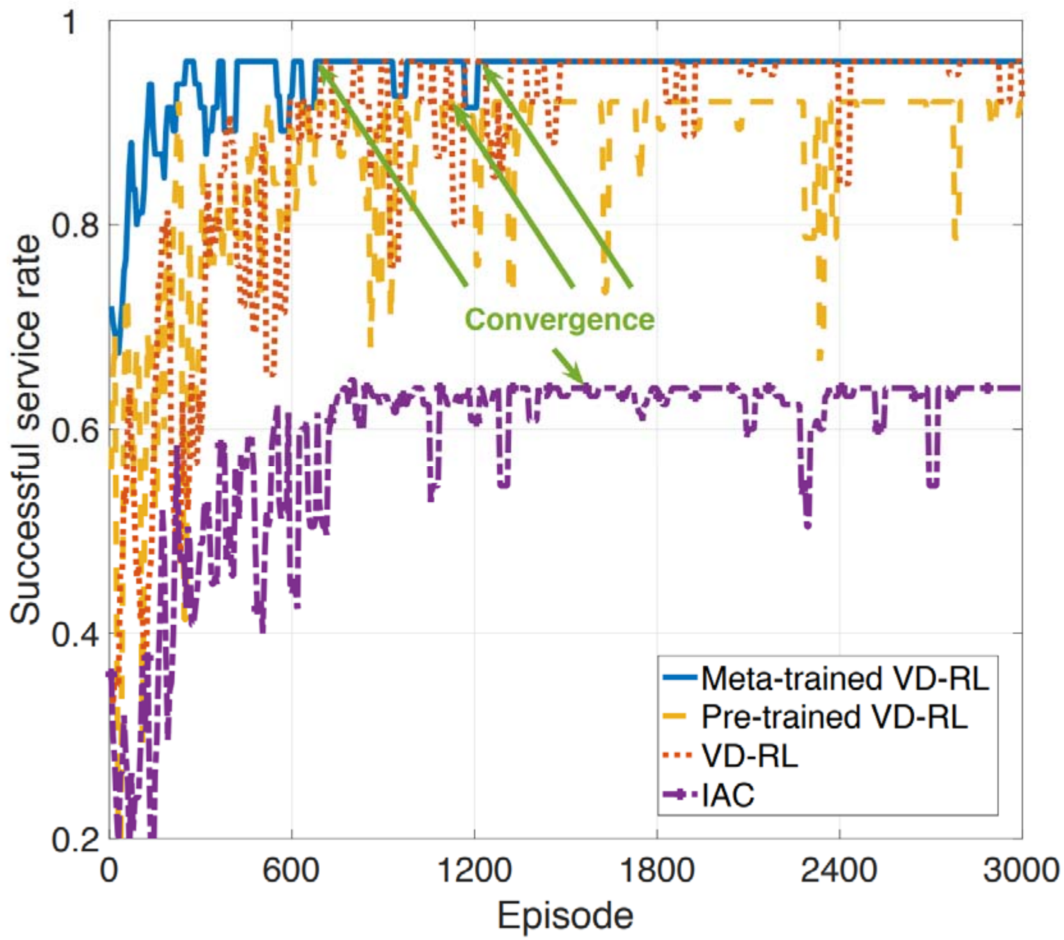
Meta-Trained Distributed Value Decomposition Reinforcement Learning

- We build a novel meta-RL framework that merges the advantages of value decomposition, policy gradient, and meta-learning
- **Decompose** to reduce **complexity**, **meta-train** to improve **generalizability**



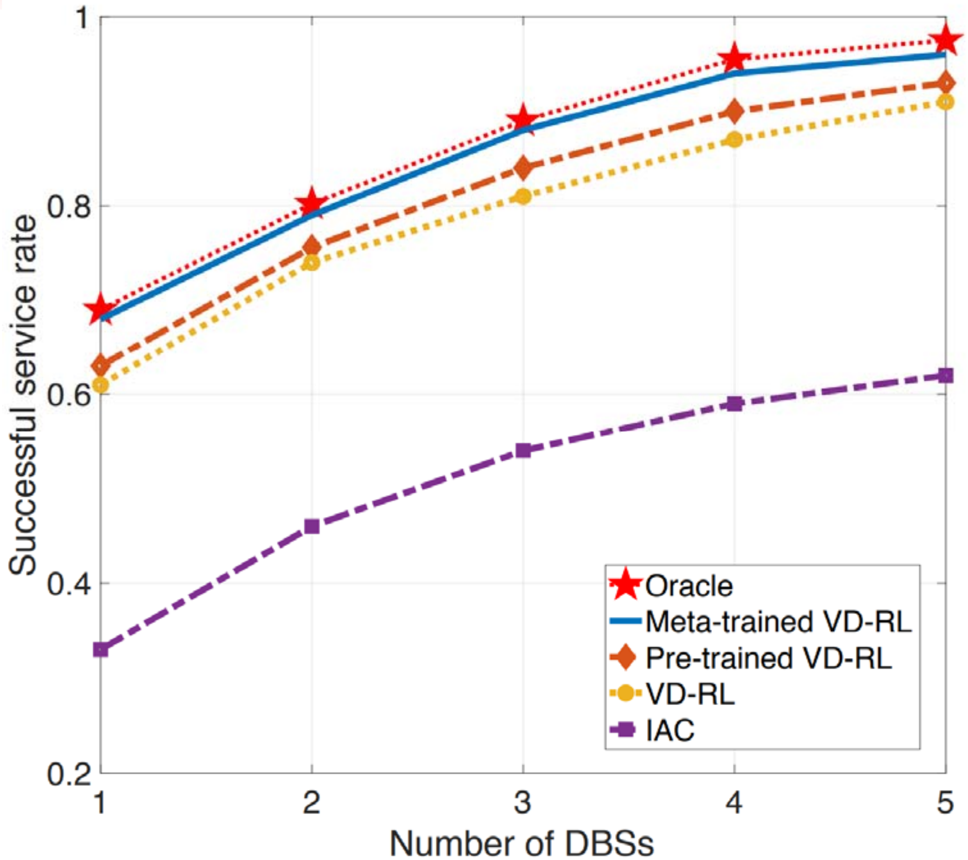


Simulation Results



- Proposed approach significantly faster than all prior algorithms, including our own without meta-training

Simulation Results

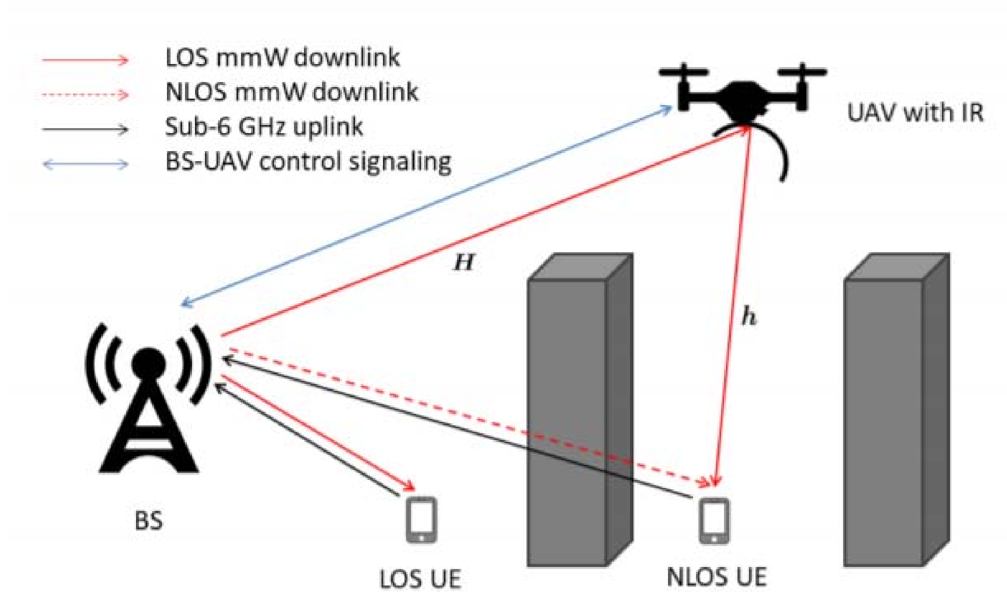


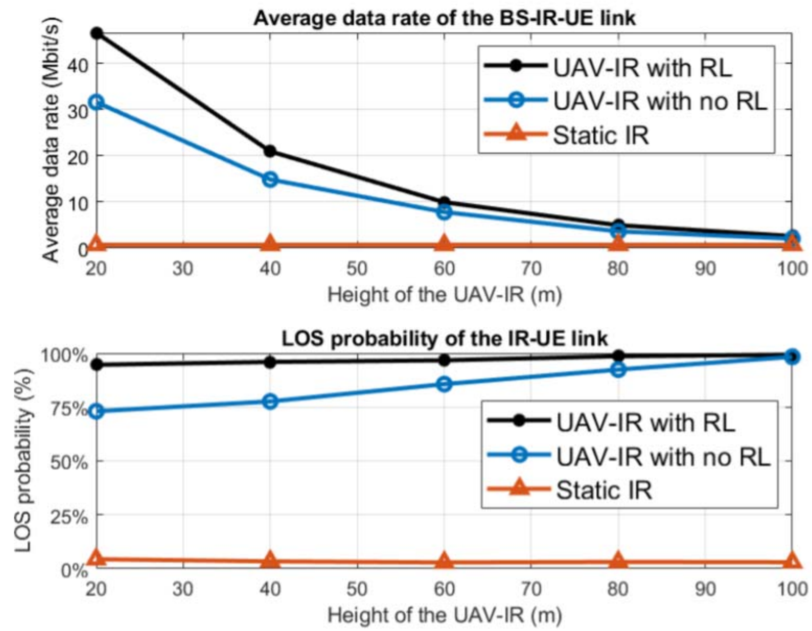
- Y. Hu, M. Chen, W. Saad, H. V. Poor, and S. Cui, "Distributed Multi-agent Meta Learning for Trajectory Design in Wireless Drone Networks", *IEEE Journal on Selected Areas in Communications (JSAC), Special Issue on UAV Communications in 5G and Beyond Networks*, to appear, 2021.

- Proposed approach achieves a higher rate compared to all prior algorithms
- Other topics for drones?

New Use Case: Drones as Flying Intelligent Reflectors

- We were the first to propose the use of a drone as a flying intelligent reflector
  - Flexibility and agility, particularly to avoid blockage at high frequencies

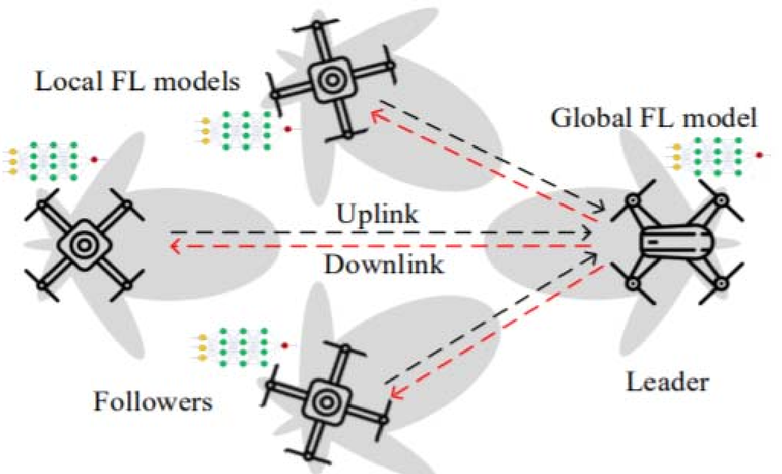




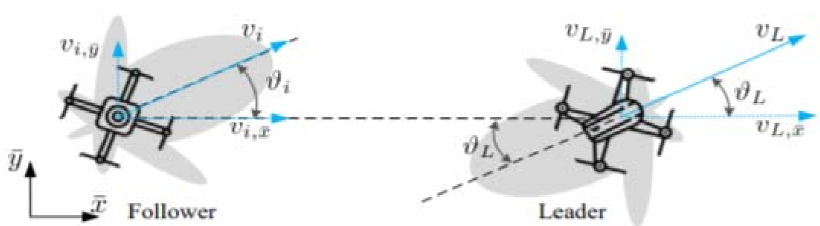
- Q. Zhang, W. Saad, and M. Bennis, "Reflections in the Sky: Millimeter Wave Communication with UAV-Carried Intelligent Reflectors", in Proc. of the IEEE Global Communications Conference (GLOBECOM), Next-Generation Networking and Internet Symposium, Waikoloa, HI, USA, December 2019.

Joint Communications, Learning, and Control

- Federated learning for communications and control in the sky with drone swarms

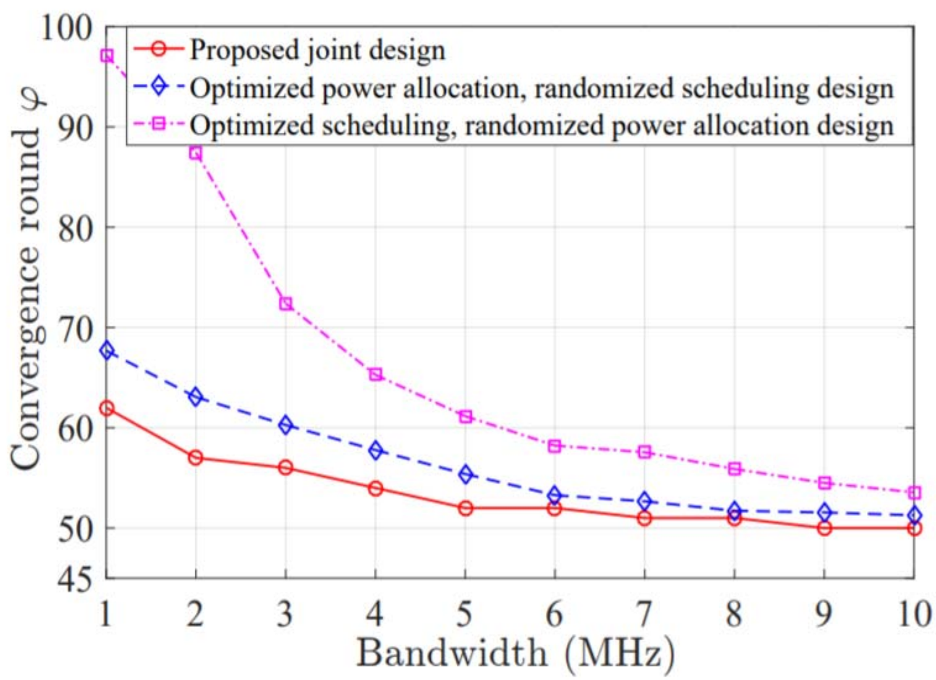


(a) Communication and learning models.

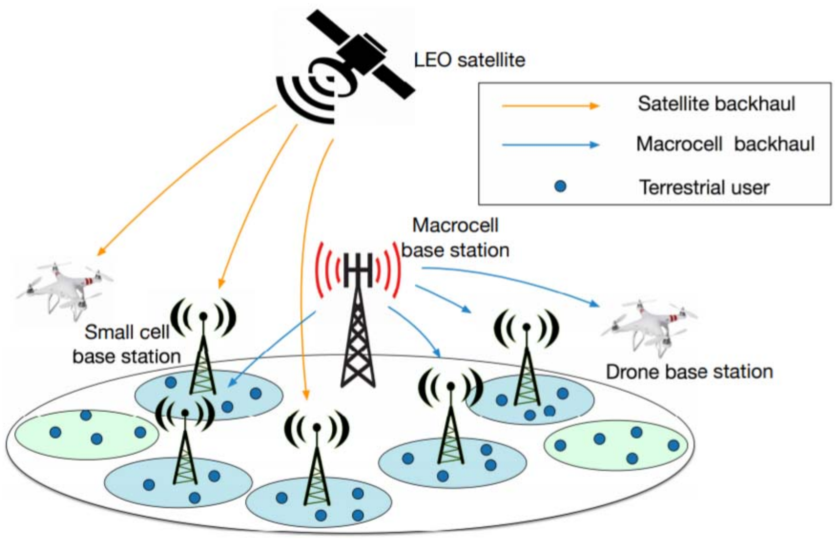


(b) Angle deviations and control system.

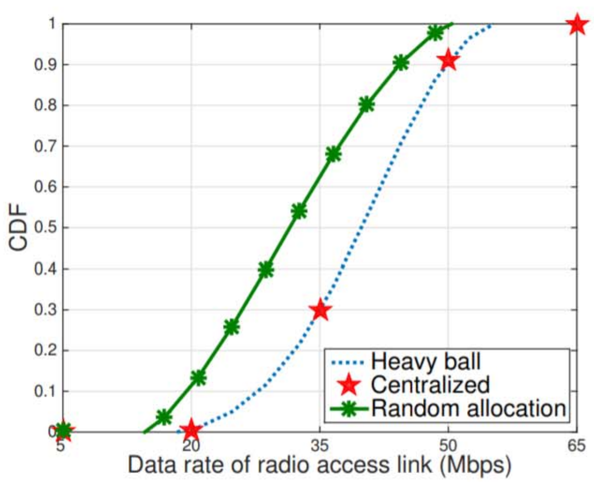
- Co-design of systems



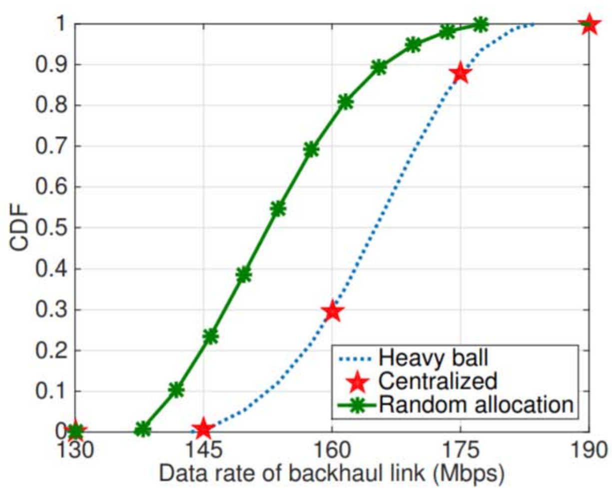
Integrated Access - Backhaul



- Joint resource allocation across access and backhaul with LEO
- Market-based approach
- Y. Hu, M. Chen, and W. Saad, "Joint Access and Backhaul Resource Management in Satellite-Drone Networks: A Competitive Market Approach", *IEEE Transactions on Wireless Communications*, 2020.

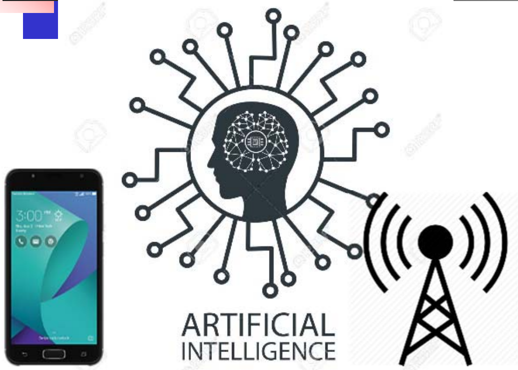


(a)



(b)

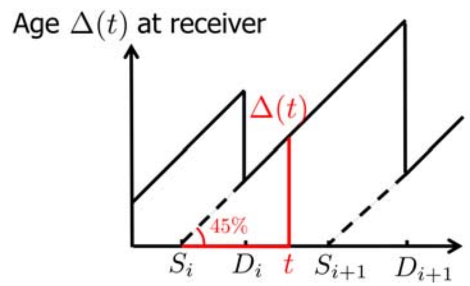
Other research areas



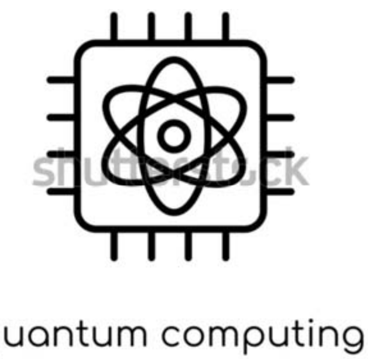
- 5G/6G/IoT systems
  - Joint sensing and comm
  - Reliable/low latency
  - Terahertz/RIS
  - Semantic communications
- AI-enabled XR
  - User experience
  - AI for wireless AR/VR
  - Holography
  - Digital twins
- Connected drones and autonomous vehicles
  - Distributed control
  - Wireless connectivity
  - CPS Security

- Reliable, generalizable, distributed learning
  - Meta-learning, curriculum learning, and training-free learning
  - Green, distributed AI (precision vs energy vs accuracy)
  - Continual, lifelong learning (brain-like)
  - Multi-agent coordination and comm.

Other research areas



- Age of information
  - Age of information in massive systems
  - Information management
  - Also links to semantic information



- Quantum computing
  - Design of quantum networks
  - New quantum learning paradigms
  - Optimization challenges

- Smart cities
  - Big data for smart city optimization
  - Air pollution
  - Security

- Game theory
  - Foundations and behavioral game theory (bounded rationality)
  - Applications to AI, CPS, security, policy, wireless, water networks, etc.

Conclusions

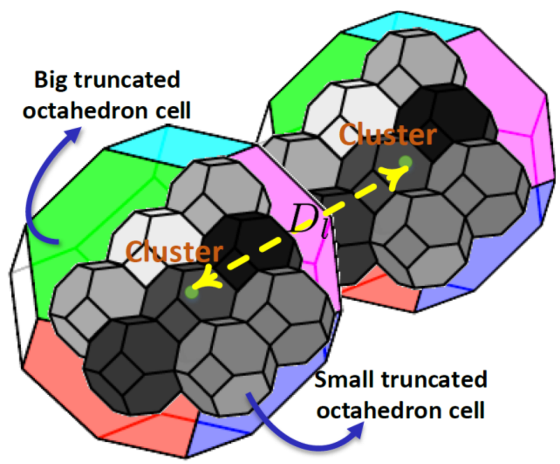
- Future networks will inevitably be 3D, but the fundamental question remains on whether this will be a “mere feature” or a fully-fledged network design
- Drones are clearly disruptive to wireless networks
  - Need for new communication and control paradigms
- Confluence of four key enablers: communications, control, AI, and security
  - These fields are now convergent, and no longer distinct
- ***Towards flying cities?***
  - ***Human meets machine meets data, for the well-being of humans (at least we hope so ☺)!***

Finally....

Communications

Thank You
Questions?

Control



Autonomy