ISWCS 2018 - Tutorial

Wireless Communications and Networking with Unmanned Aerial Vehicles

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Outline

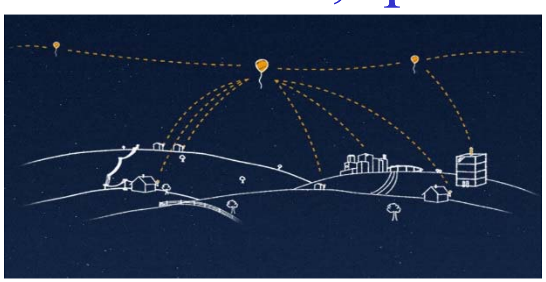
- Introduction and motivation
- **Part I:** Channel modeling for UAVs
- **Part II:** Performance analysis and tradeoffs
- **Part III:** Optimal deployment
- **Part IV:** Resource management for UAVs
- **Part V:** Security
- Concluding remarks

The inevitable rise of the UAV

Few facts:

- The number of UAVs will skyrocket from few hundreds in 2015 to 230,000 in 2035
- Different types of aerial objects/systems, LOS, BLOS
- Includes drones, LAP, HAP, balloons, quadcopters, etc

OneWeb LEO constellation: 648 low-weight, low orbit and low latency satellites positioned around 750 miles above Earth ...+ SpaceX from E. Musk



Google Project LOON

Matternet

Facebook Project Aquila

Unmanned Aerial Vehicles

- Can be a small plane, balloon or drone
  - High altitude platform (HAP) above 15 km, or Low altitude platform (LAP) between 200 m to 6 km
  - Proposals from Facebook, Google, spaceX to connect the unconnected
- Frequency bands for HAPs: 38-39.5GHz (global), 21.4-22 GHz and 24.25-27.5GHz (region-specific)
- Remotely controlled or pre-programmed flight path
- Control and non-payload communication (CNPC) systems

c) that the safe flight operation of UAS needs reliable communication links and associated spectrum, especially for the remote pilot to command and control the flight and to relay the air traffic control communications, also referred to as control and non-payload communications (CNPC);

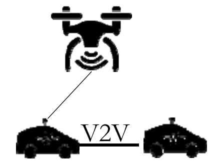
RESOLUTION 153 (WRC-12)

Countless Applications

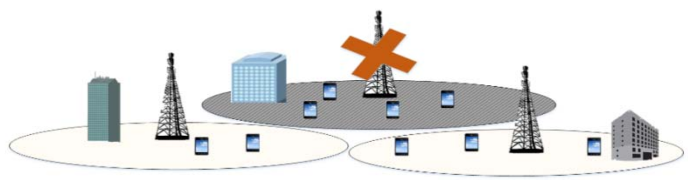
VR

- Applications
  - Communications, disaster management, search and rescue, security, control, agriculture, IoT, etc
  - Covering hotspots

  \+ 1000x more



Smarter mobility

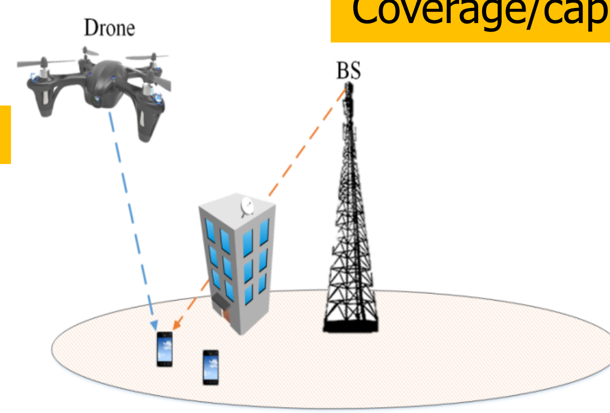


disaster

- Advantages
  - Adjustable altitude
  - Potential Mobility
  - Low infrastructure low cost
  - Limited available energy for Drones
- Also, many challenges

Agriculture

Coverage/capacity

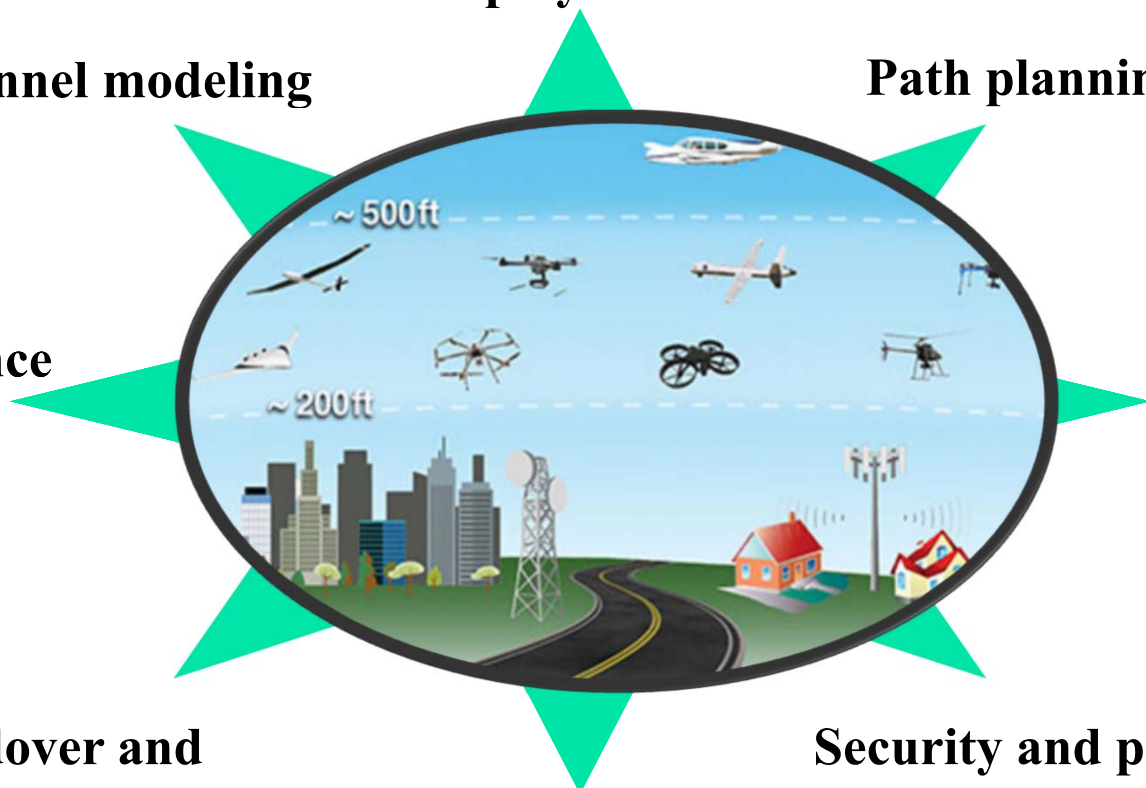


Challenges

Deployment

Channel modeling

Path planning/mobility



Interference

Energy efficiency

Handover and
moving cells

Resource
management

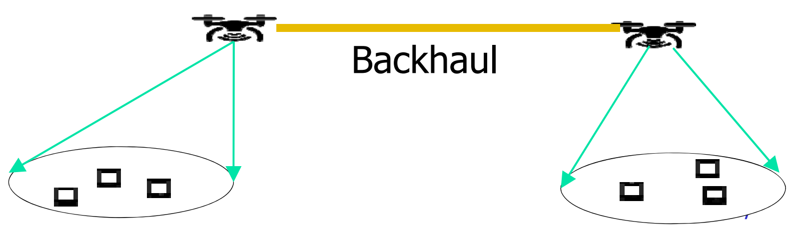
Security and privacy

Wireless Back-/Fronthauling

- UAV-to-UAV communication required for coordination, interference mitigation, relaying, routing in the air, etc.
- Satellite and WiFi considered as candidate technologies for providing wireless backhauling→ depending on latency-bandwidth requirements
- Satellite backhauling brings the advantage of unlimited coverage offering the possibility of connecting the aerial network for any distance
  - However, the latency introduced by the satellite links (GEO) may affect some real time services such as voice and real-time video.
- To avoid satellite delays and the cost, WiFi links can be used albeit reduced coverage and capacity (doubtful QoS guarantees..)

Recent interest in Free Space Optics

- License free PtP narrow beams
- But tackle rain, fog and cloud attenuations
- Multi-connectivity to the rescue..?



Tools Usefuls for UAVs

5G+

Random matrix theory

- Asymptotics

Stochastic optimization

- CSI/QSI uncertainties

Stochastic geometry

- BS/UE location

Game theory (GT) and learning

- Decision making
- Resource management
- Clustering
- Supervised, non-supervised learning

Control Theory

- Lyapunov
- Consensus

Transport Theory

- Association
- Mobility

Physics

- Mean field
- Random graph

Economics

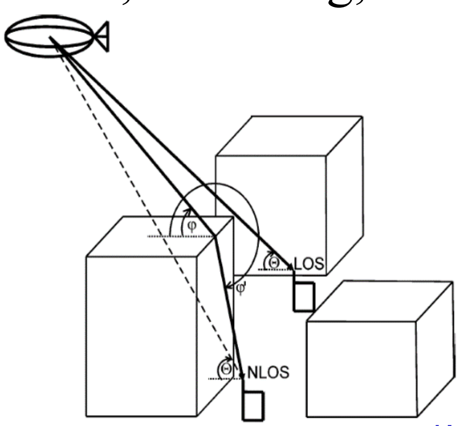
- Matching theory
- Pricing

⇒In this tutorial, we will (briefly) touch on GT, optimal transport, and learning

Part I –
Air-to Ground Channel Modeling for UAVs

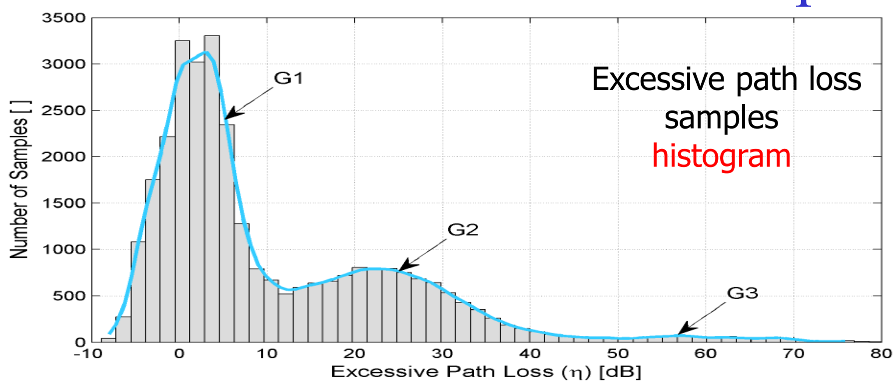
Air-to-Ground AtG Channel Model

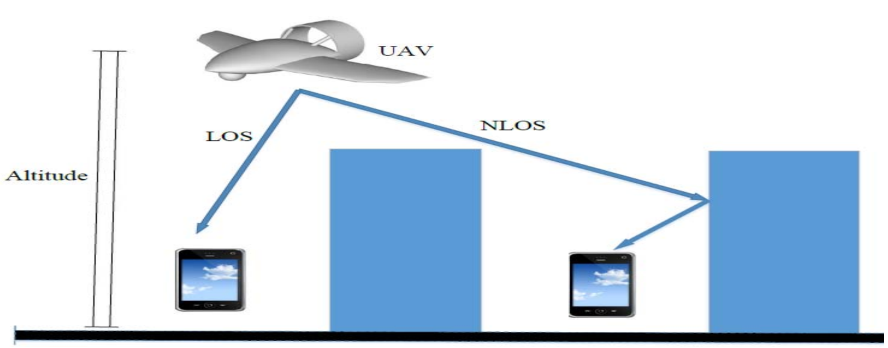
- Radio propagation in AtG channel differs from terrestrial propagation models
- Typically radio waves in AtG channel travel freely without obstacles for large distances before reaching the urban layer of man-made structures.
- UAV-ground channels typically include:
  - Line-of-sight (LOS) and NLOS links
  - A number of multi-path components (MPC) due to reflection, scattering, and diffraction by mountains, ground surface, foliage
- Common models define a LOS probability between UAV and ground user that depends on:
- Environment (suburban, urban, dense urban)
- Height (h) and density of the buildings (building/km2)



Air-to-Ground Channel Model

- Received signals include:
  - Line of sight (LOS): strong signal (G1)
  - Non-line of sight (NLOS): strong reflection (G2) or fading (G3)
- Each group with a specific probability and excessive loss
- Dominant components
  - LOS links exist with probability *P and* NLOS links exist with probability *1-P*
  - Consider LOS/NLOS separately with different path loss values





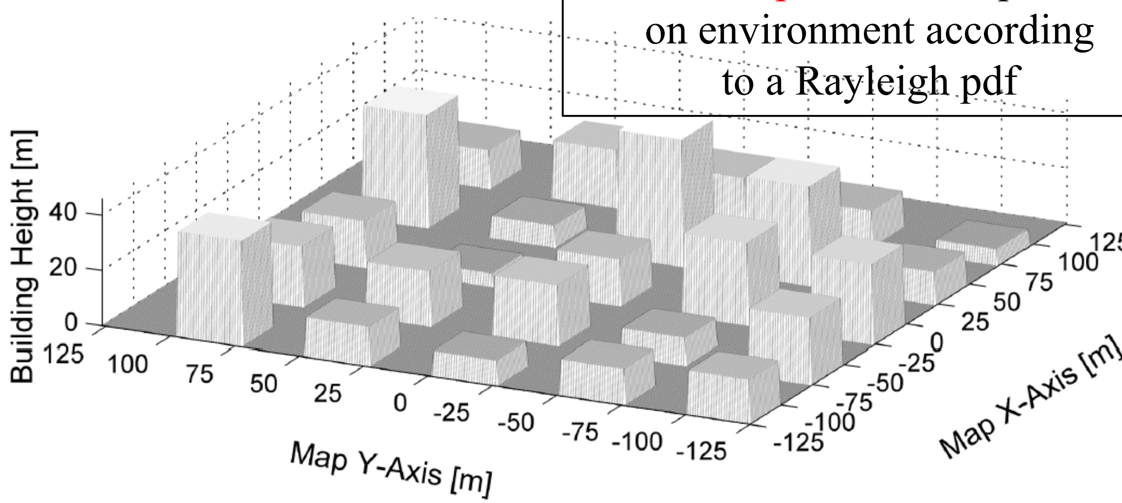
Air-to-Ground Channel Model

- Model by Al-Hourani et al.
- Buildings and environment impact the propagation
  - Distribution of buildings' heights:

$$\mathbf{P}(h) = \frac{h}{\gamma^2} \exp\left(\frac{-h^2}{2\gamma^2}\right)$$

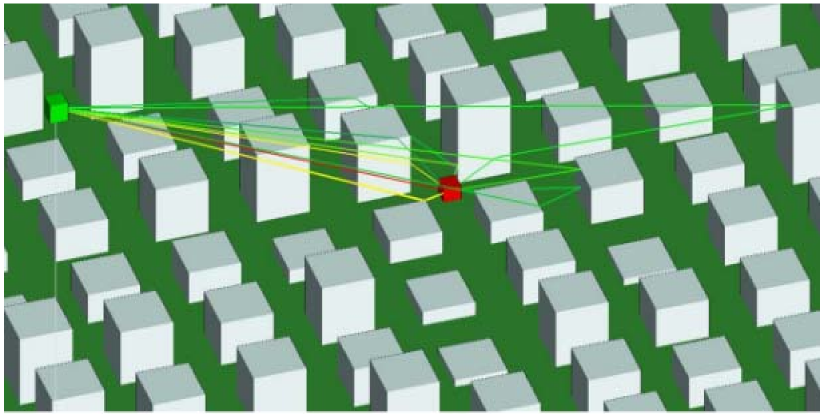
  - Suburban
  - Urban
  - Dense urban
  - Highrise urban

A scale parameter depends on environment according to a Rayleigh pdf



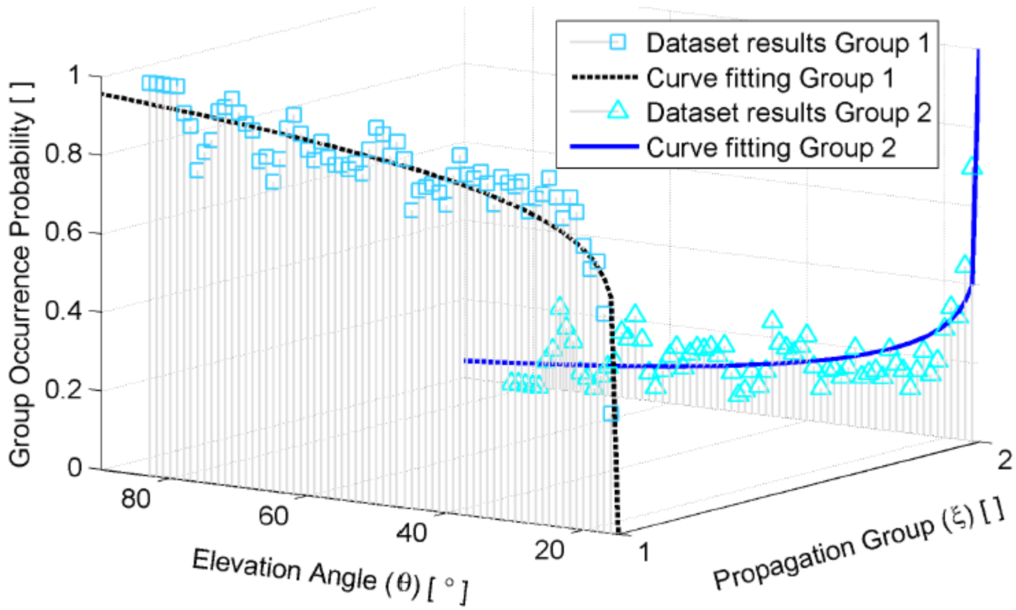
Ray Tracing Simulation

- Allows the prediction of signal strength in an accurate manner
- Based on a simulation of actual physical wave propagation process
  - Can consider different ray types: Direct, Reflected and Diffracted rays
- Requires buildings database
- 3D predictions



Ray Tracing Simulation

- Propagation Group Occurrence Probability, obtained at frequency = 2 GHz for an urban environment
  - Group 1: LOS
  - Group 2: NLOS



➢ Occurence probability of a certain propagation group at a certain angle

Example of a group occurrence curve fitting for two groups

Back to LOS Probability

- In urban environments, the LOS probability is given as:

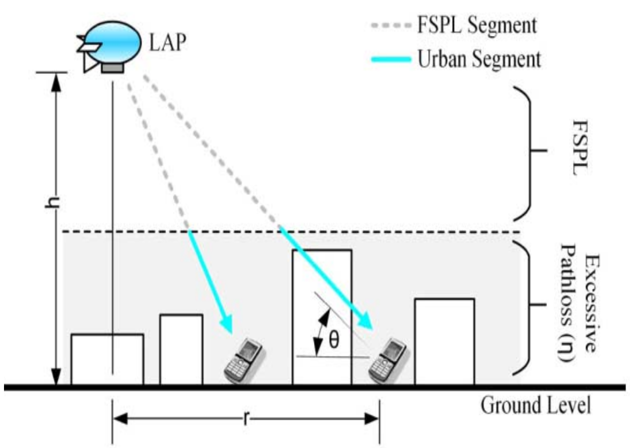
$$m = \text{floor}(r\sqrt{\alpha\beta} - 1)$$

$$\mathbf{P}(\text{LoS}) = \prod_{n=0}^{m}\left[1 - \exp\left(-\frac{\left[h_{\text{TX}} - \frac{(n+\frac{1}{2})(h_{\text{TX}}-h_{\text{RX}})}{m+1}\right]^2}{2\gamma^2}\right)\right]$$

Antenna height

Parameter depends on environment

…For large values of h, P(LoS) is a continuous function of θ and environment parameters ➔ see next slide



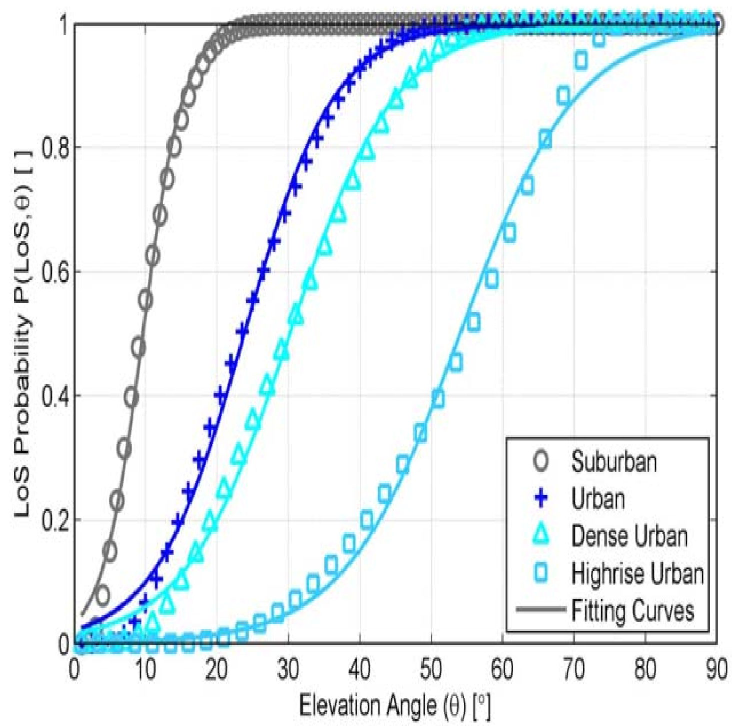
α ratio of built-up land area to the total land area

β mean number of buildings per unit area (buildings/km^2)

LOS Probability approximation

- Probability of having LOS link:
  - Trend approximated to a simple modified Sigmoid function (S-curve)
  - Increasing LOS probability

by increasing elevation angle or UAV's altitude



$$P_{\text{LOS}} = \frac{1}{1 + C\exp(-B\,[\theta - C])}$$

B and *C*: constants that depend on the environment

θ: Elevation angle

Shadow Fading

- Modeling shadow fading

Shadow fading

$$P_r(dB) = \begin{cases} P_t + G_{dB} - L_{dB} - \psi_{\text{LoS}} & \text{LoS link,} \\ P_t + G_{dB} - L_{dB} - \psi_{\text{NLoS}} & \text{NLoS link,} \end{cases}$$

Received signal power

$$\psi_{\text{LoS}} \sim N(\mu_{\text{LoS}}, \sigma^2_{\text{LoS}}) \text{ and } \psi_{\text{NLoS}} \sim N(\mu_{\text{NLoS}}, \sigma^2_{\text{NLoS}})$$

Gaussian distribution

$$\sigma_{\text{LoS}}(\theta) = k_1 \exp(-k_2\theta),$$
$$\sigma_{\text{NLoS}}(\theta) = g_1 \exp(-g_2\theta),$$

Parameters depend on environment

	700 MHz			
	Suburban	Urban	Dense Urban	Highrise Urban
μ_1	0.0	0.6	1.0	1.5
μ_2	18	17	20	29
(a_1,b_1)	(11.53, 0.06)	(10.98, 0.05)	(9.64, 0.04)	(9.16, 0.03)
(a_2,b_2)	(26.53, 0.03)	(23.31, 0.03)	(30.83, 0.04)	(32.13, 0.03)

Ricean channel model

- Small scale fading is described by the Rician distribution due to the presence of a strong LOS component in the AtG channel
- Distribution of the received signal amplitude:

$$f(r) = \frac{r}{\sigma^2} \exp\left(-\frac{r^2 + a^2}{2\sigma^2}\right) I_0\left(\frac{ra}{\sigma^2}\right) \quad (r \geq 0)$$

Average multipath component power

LOS amplitude

Bessel function

- Rician K factor: $K = \frac{a^2}{2\sigma^2}$
  - Depends on the environment
  - Lower for denser environments

L-Band→Ricean K-factors = 12 dB and 27.4 dB in C-band in the near-urban environment.

14 dB in L-band and 28.5 dB in C-band for the suburban settings.

Way forward

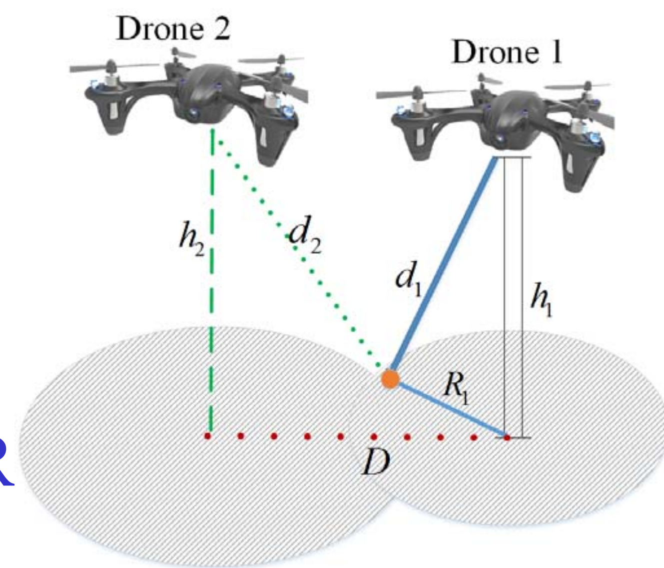
- Air-to-air channel models (still lacking in literature)
- The probabilistic model may not be the best, real-world measurements can help
- Airframe shadowing for large-sized or small-sized aircraft, tree/building shadowing at low altitude small UAV, also terrain shadowing for mountainous scenarios or beyond LOS conditions
  - Of relevance here are the works of Matolak and NASA
- How to integrate multiple antennas, what is the most adequate number of elements and their location (MIMO or mmWave air-to-ground channels?)

Part II – Performance Analysis

Drone small cells in the clouds: Initial insights on design and performance analysis

System Model

- Downlink scenario
- Drones provide coverage for a target area
- Scenarios:
  - Single drone
  - 2 drones without interference
  - 2 drones with intercell interference



- Target: Meeting the minimum SINR requirement on the ground

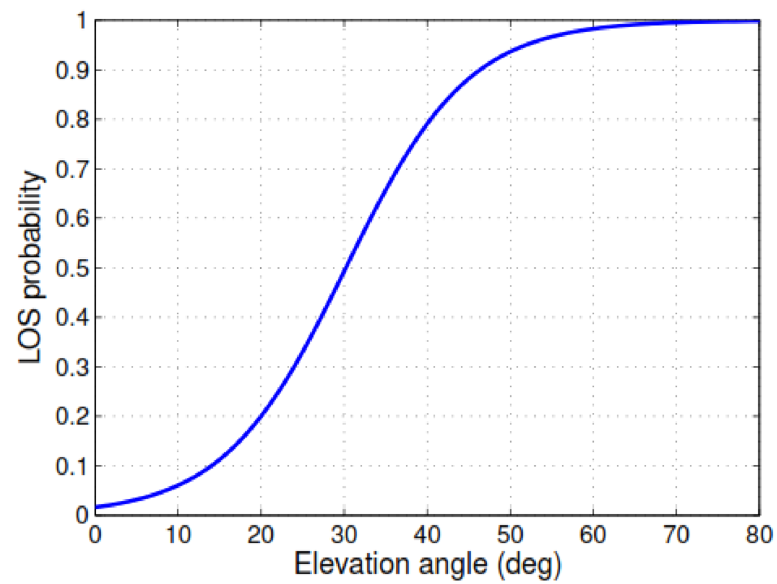
Main Goals

- Determining the optimal altitude of drones
  - Leading to maximum coverage
  - Full coverage using minimum transmit power for the drones
- Optimal deployment of two interfering drones
  - Distance between the drones?
  - Altitudes?
- Highlighting tradeoffs while deploying drones
  - Interference, coverage, transmit power

Impact of Drone's Altitude

- Higher altitude: Higher path loss vs. higher LOS proba.
- Lower altitude: Lower path loss vs. more NLOS
- Altitude and flight constraints
  - Higher and lower altitudes are bounded

What is the Optimal Altitude?



Single Drone

- Minimize transmit power via an optimal altitude
- Path loss as a function of elevation angle:

Additional loss for NLoS

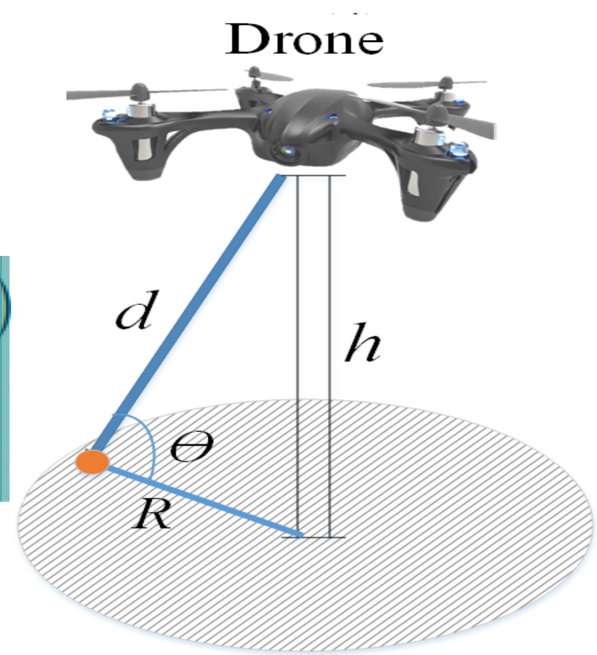
$$\overline{L}(\theta) = \frac{-\eta}{1 + \alpha \exp(-\beta \left[\frac{180}{\pi}\theta - \alpha\right])} - 20\log(R\cos(\theta)) + 20\log(\frac{4\pi f_c d}{c})$$

Environmental parameters

$$h^* = \arg\min_h P_t(h, R, \gamma_{\text{th}})$$

$$h_{\min} \leq h \leq h_{\max}$$

Optimal altitude



Optimal Altitude

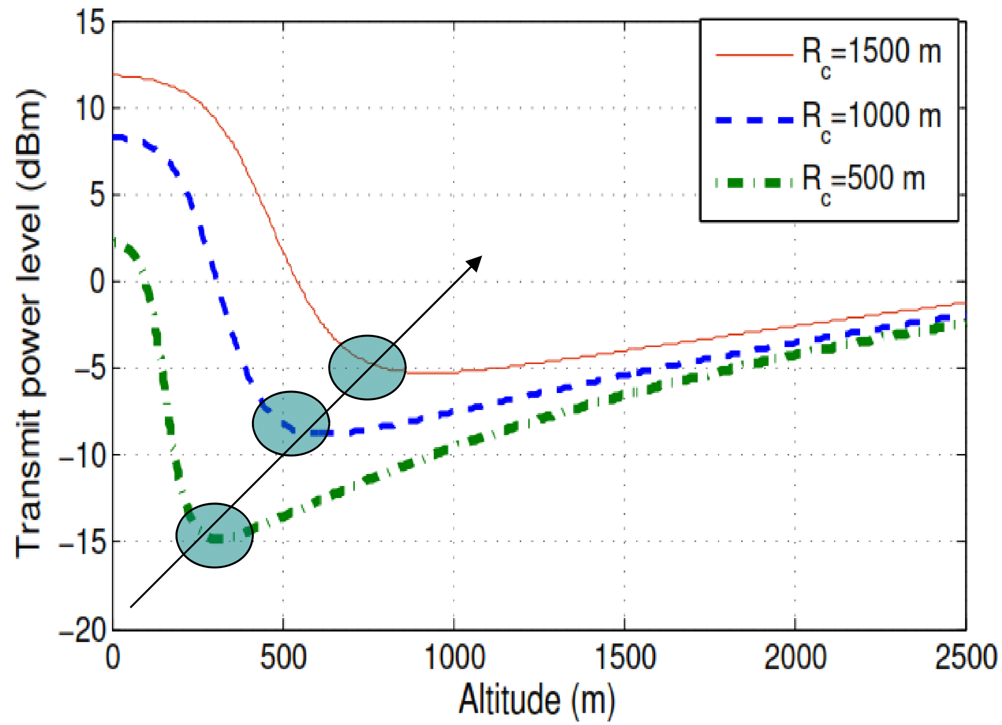
- Optimal altitude depends on the area size (R_c)
  - Increasing drone's altitude to service larger areas

@Low-altitude: high shadowing
+ low LOS probability →coverage radius decreases

@ **high-altitude**: high LOS probability but PL
Increases –> Coverage decreases

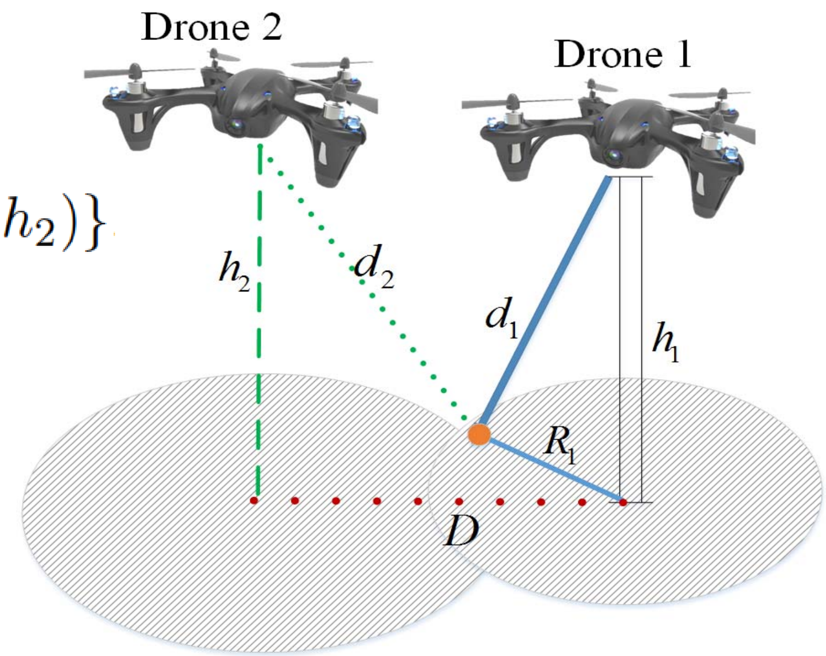
E.g.; optimal altitude for providing 500m coverage radius while consuming min. tx power is 310 meters

Altitude increases w/ coverage radius



Two Drones

- Given a desired geographical area:
- Maximize the total coverage area
- What is the distance between drones?
- What is their altitude?



$$(D_{\text{opt}}, h_{1,\text{opt}}, h_{2,\text{opt}}) = \underset{D,h_1,h_2}{\arg\max}\{A_C(D, h_1, h_2)\}$$

Distance between drones

Total coverage

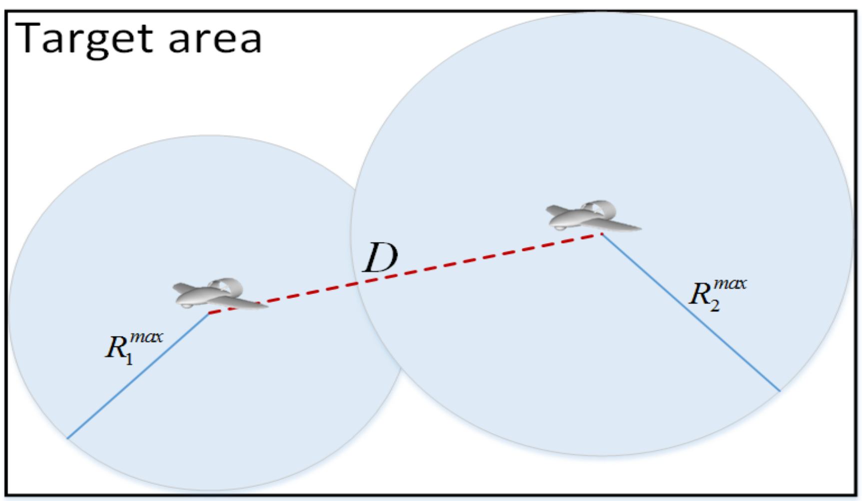
No Interference Case

- Deploying each drone at its optimal altitude
- Packing the coverage areas inside the target area
- While keeping the distance between drones as far as possible, but inside the target area

$$A_C^{\max} = 2\pi(R^{\max})^2 - 2(R^{\max})^2\cos^{-1}\left(\frac{D}{2R^{\max}}\right) + \frac{D}{2}\sqrt{4(R^{\max})^2 - D^2}$$

Total coverage

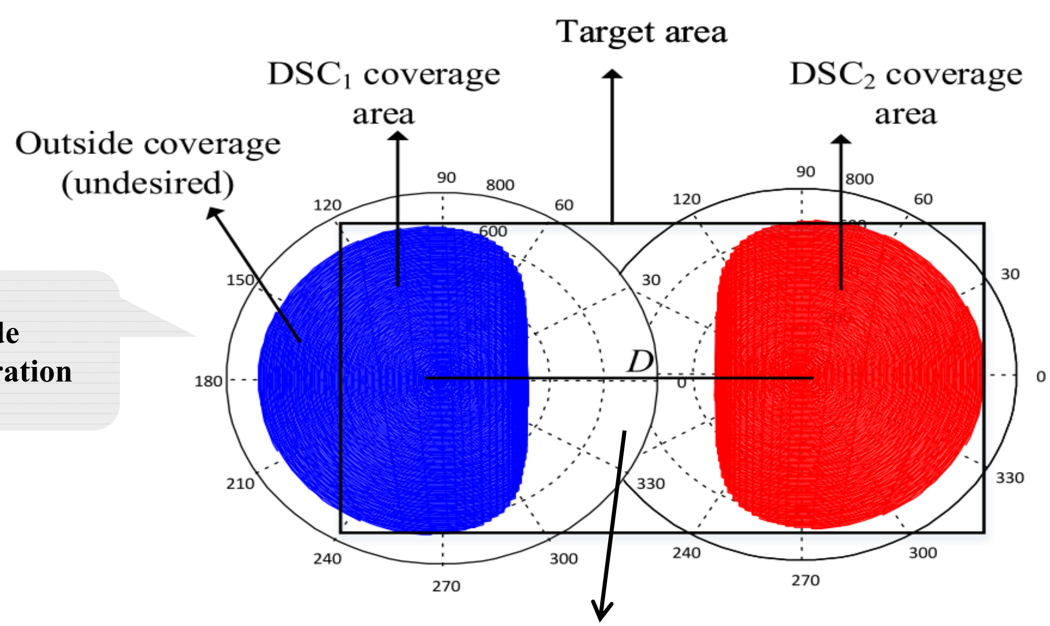
Maximum coverage range of each drone



Two Interfering Drones

- Consider a rectangular geographical area
- High distance between drones: covering undesired area
- Small distance between drones: high interference

- **300 meter altitude**
- **1100 meter separation**



- No coverage in between due to the interference
  - Drones should not be placed too close

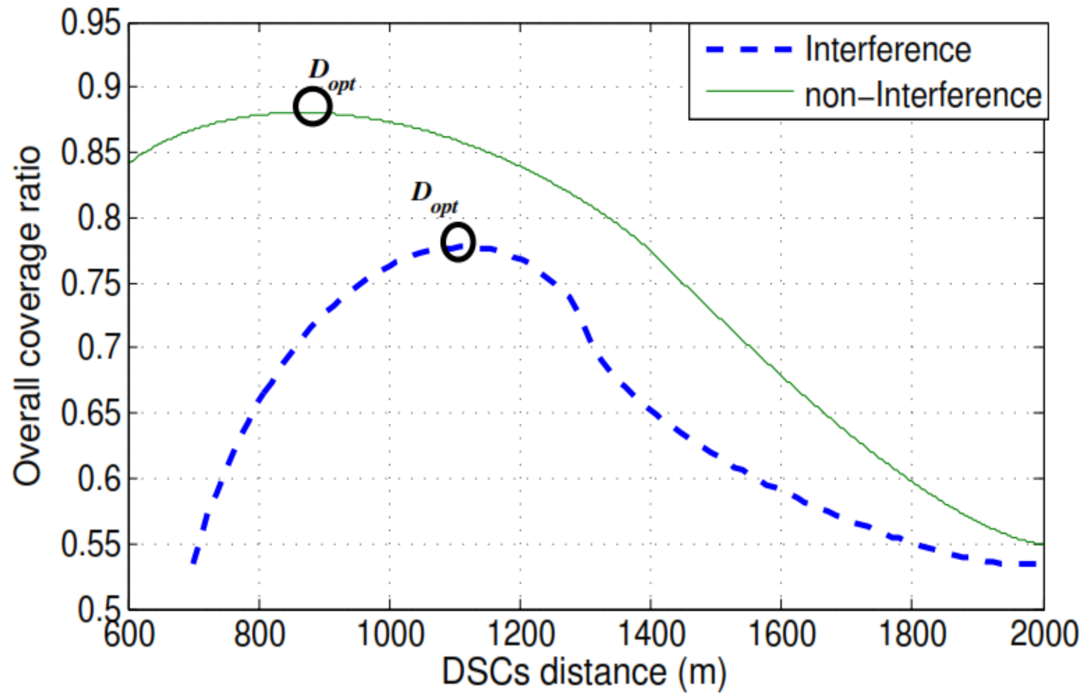
Results

- Bounded target geographical area
- Existence of optimal drones' separation distance for maximum coverage

At high drone distance, although separated, coverage ratio is low (undesired)

Likewise, if too close interference increases.

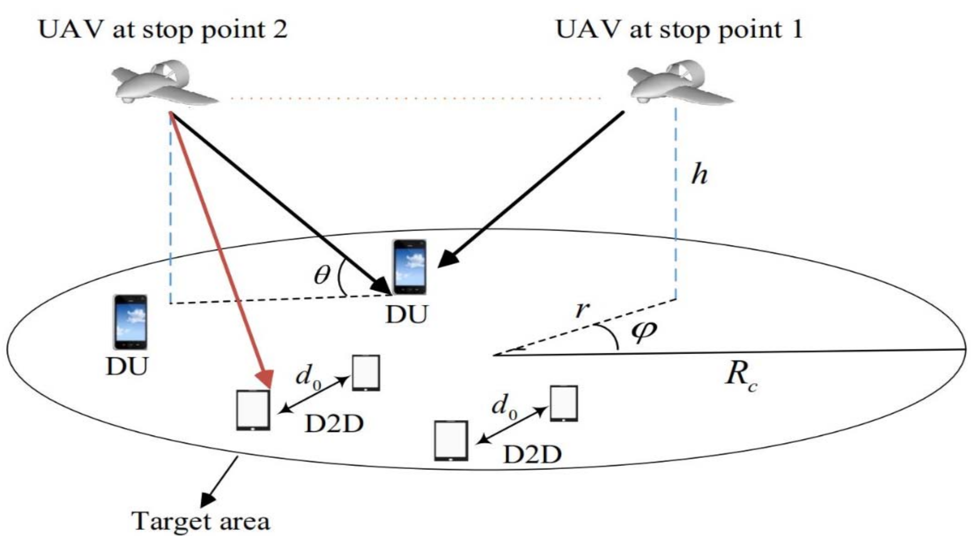
→optimal separation distance exists!



Unmanned Aerial Vehicle with Underlaid Device-to-Device Communications: Performance and Tradeoffs

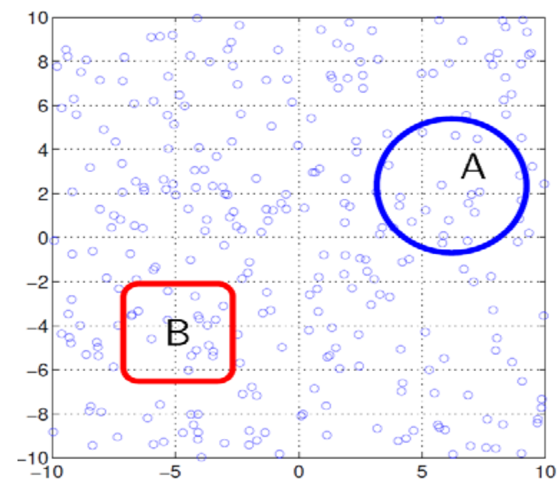
System Model

- Downlink Scenario: UAV coexists with a device-to-device (D2D) network
- Two types of users: downlink users (DU) and D2D
- UAV provides service for downlink users
- Interference between UAV and D2D transmitters
- Static and Mobile UAV Cases



UAV and D2D: Assumptions

- Users (DU and D2D) distributed based on Poisson point process (PPP)
  - Number of users follows Poisson distribution, but uniformly distributed over the area
  - The number of points in a bounded area has a Poisson distribution with mean e.g. λ×A or λ×B



- Underlay D2D communications: use existing licensed spectrum
- Can we analyze the performance tradeoffs for UAV deployment

Main Objectives

- Derive the average coverage probability and sum-rate expressions
  - Finding the relationship between UAV parameters (altitude, etc.) and rate/coverage
  - Finding some fundamental performance tradeoffs

What is the optimal altitude of the UAV that maximizes the coverage and rate?

- Fundamental tradeoffs between DU and D2D users

How to optimize coverage using UAV mobility ?

Performance Evaluation Metrics

- Coverage probability for downlink users (DUs)

$$P_{\text{cov},du}(r, \varphi, \beta) = \mathbb{P}\left[\gamma_u \geq \beta\right]$$

Polar coordinates

SINR Threshold

SINR

- Coverage probability for D2D users

$$P_{\text{cov},d}(r, \varphi, \beta) = \mathbb{P}\left[\gamma_d \geq \beta\right]$$

- Average rates

$$\bar{C}_{du} = W \log_2(1 + \beta) \bar{P}_{\text{cov},du}(\beta),$$

$$\bar{C}_{d} = W \log_2(1 + \beta) \bar{P}_{\text{cov},d}(\beta),$$

Static UAV: Analytical Results

- D2D Coverage Probability

$$P_{\mathrm{cov},d}(r,\varphi,\beta) = \exp\left(\frac{-2\pi^2\lambda_d\beta^{2/\alpha_d}d_0^2}{\alpha_d\sin(2\pi/\alpha_d)} - \frac{\beta d_0^{\alpha_d}N}{P_d}\right)$$

$$\times\left(P_{\mathrm{LoS}}\exp\left(\frac{-\beta d_0^{\alpha_d}P_u|X_u|^{-\alpha_u}}{P_d}\right) + P_{\mathrm{NLoS}}\exp\left(\frac{-\beta d_0^{\alpha_d}\eta P_u|X_u|^{-\alpha_u}}{P_d}\right)\right)$$

Distance Between D2D pairs

UAV-D2D distance

D2D density

LoS probability

D2D transmit power

UAV transmit power

- DU Coverage Probability

$$P_{\mathrm{cov},du}(r,\varphi,\beta) = P_{\mathrm{LOS}}(r)\mathbb{P}\left[\frac{P_u r^{-\alpha_u}}{I_d+N}\geq\beta\right] + P_{\mathrm{NLOS}}(r)\mathbb{P}\left[\frac{\eta P_u r^{-\alpha_u}}{I_d+N}\geq\beta\right]$$

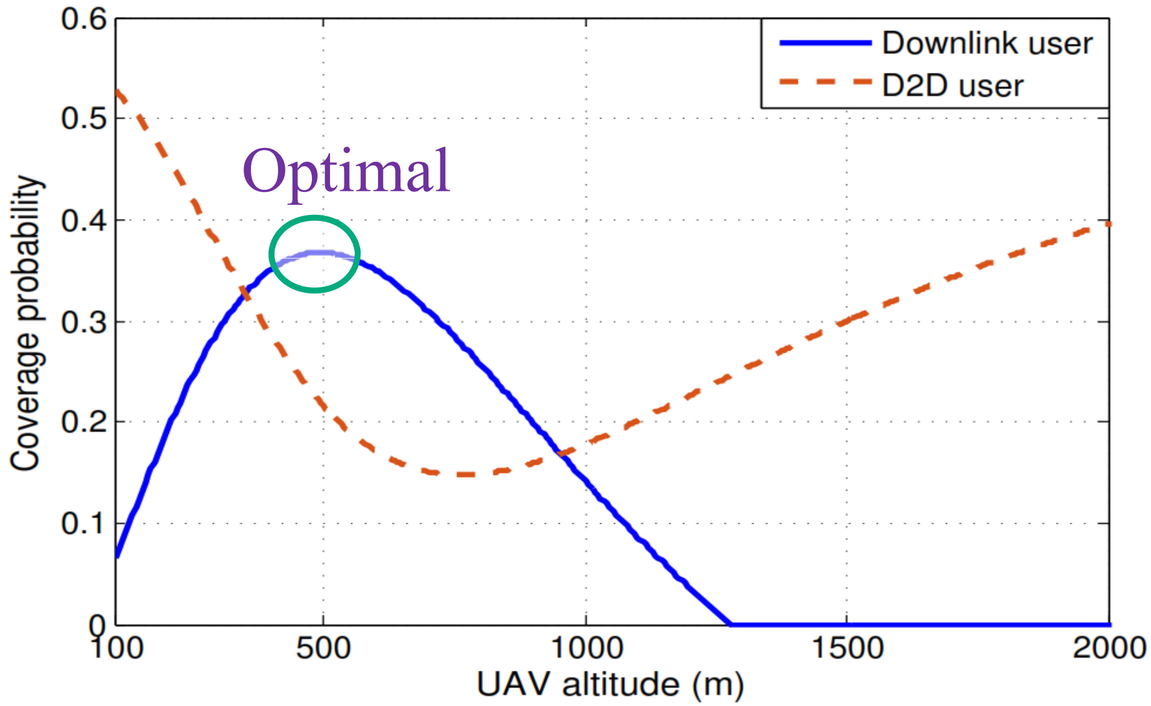
Interference from D2D links

Key parameters

- Number of D2Ds
  - Impacts interference generated at the DUs
- Distance between each D2D pair
- UAV's location and altitude
  - Impacts air-to-ground channel
- Transmit powers of D2D and UAV
  - Directly affect the coverage probabilities
- SINR threshold
- Overall, we have a tractable expression to analyze UAV coverage

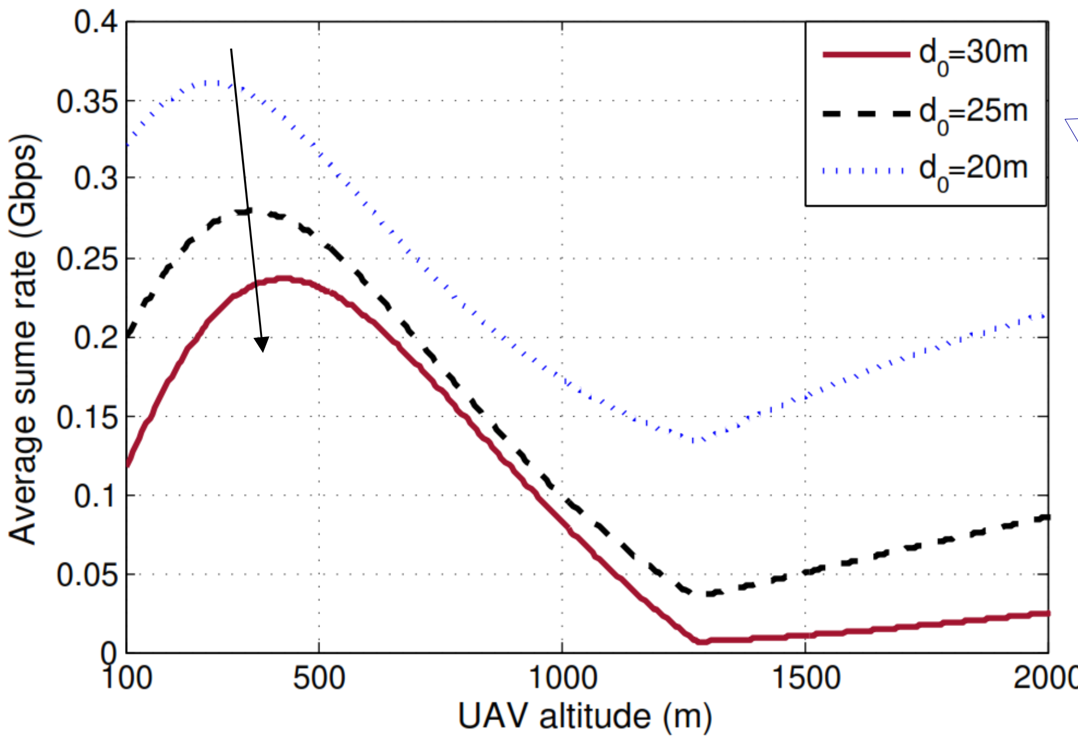
Results: Static UAV

- Optimal altitude for DU maximum coverage
  - LoS and NLoS tradeoff
- Impact of altitude on D2D coverage probability
  - UAV is an interference source for D2D



Results: Static UAV

- Average sum rate vs. altitude
  - Considering DU and D2D rates
  - Depends on the distance between each D2D pair (d_0)



The lower is d_0 the higher is the sum-rate

Mobile UAV

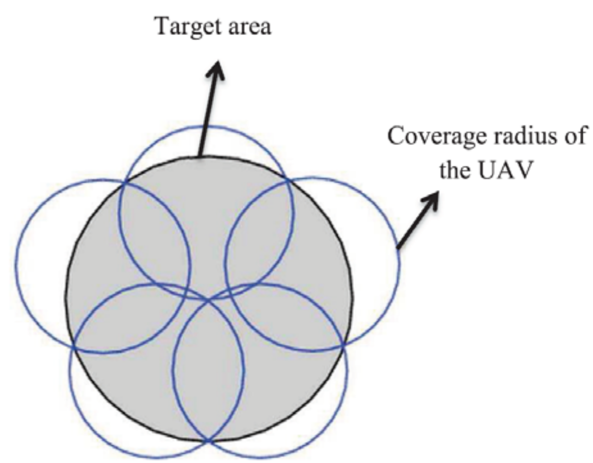
- UAV moves over the target area
- Transmits at given geographical locations: "stop points"

- Goal: satisfy DUs coverage requirements by covering the entire area
- Analyze the impact of UAV's mobility on the outage probability of D2D links
  - Considering the spatial correlation in D2D communications

Question: What is the minimum number of stop points (delay)?

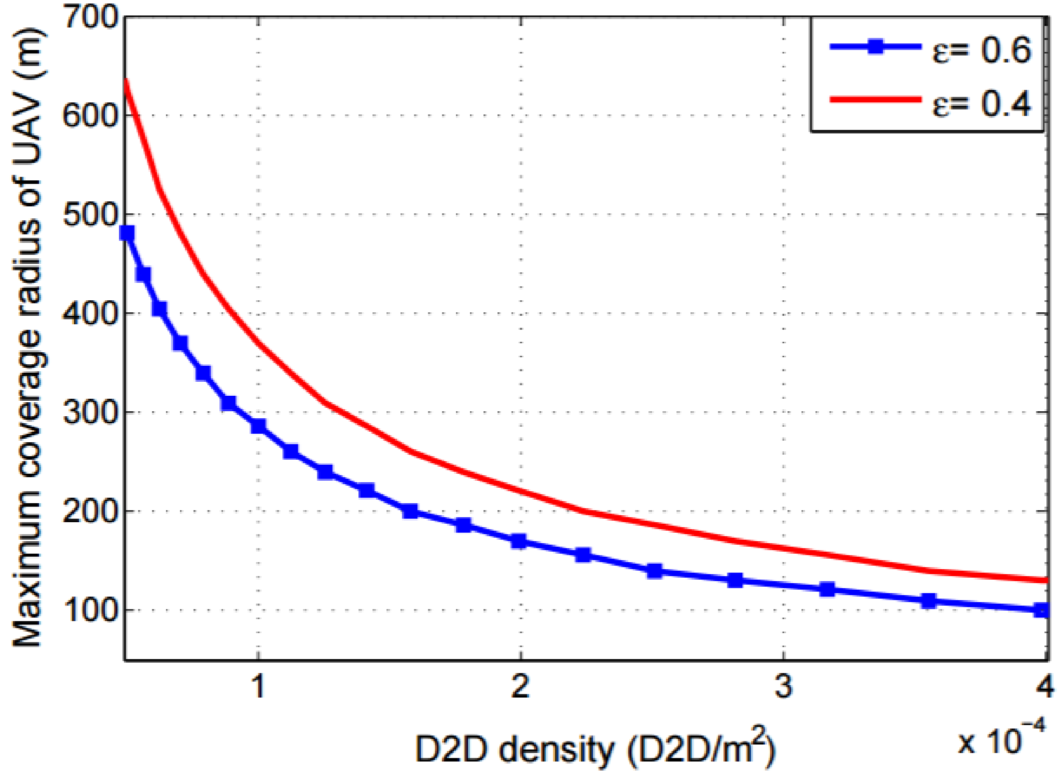
Mobile UAV

- Minimum number of stop points
  - Depends on: UAV altitude, D2D density, size of area, coverage constraint
- Moving the UAV to provide complete coverage for the area of interest
  - Using optimal circle covering approach
  - Full coverage with minimum number of circles



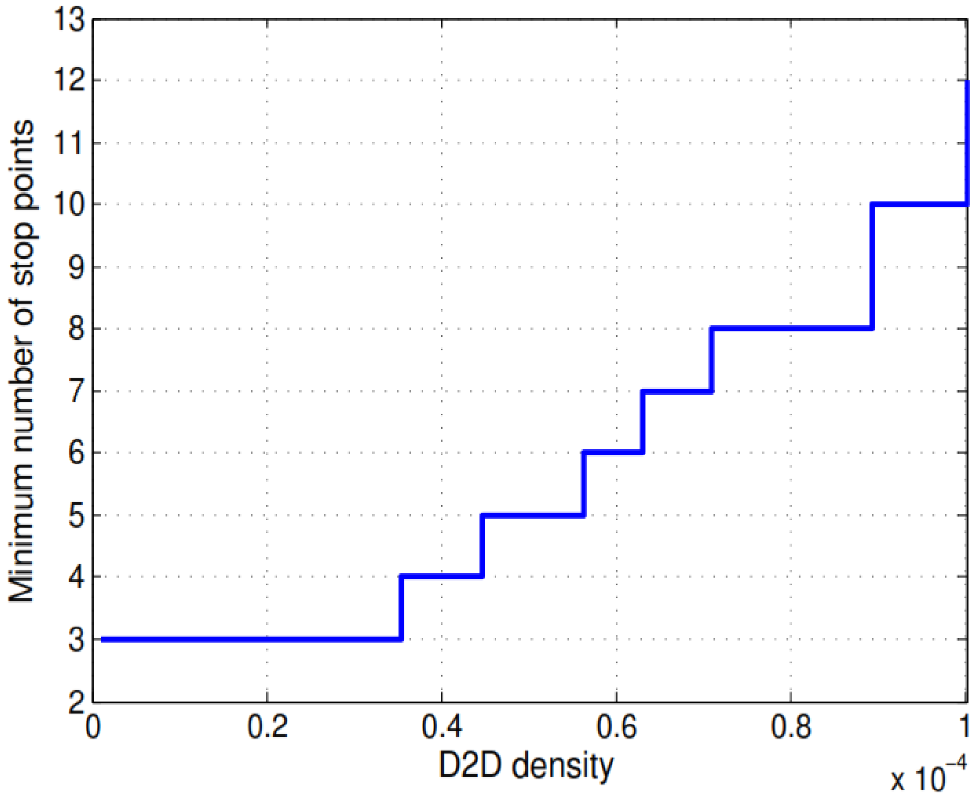
Results: Mobile UAV

- Maximum coverage radius vs D2D density
  - Higher number of D2Ds: higher interference
    - Decreasing coverage radius!



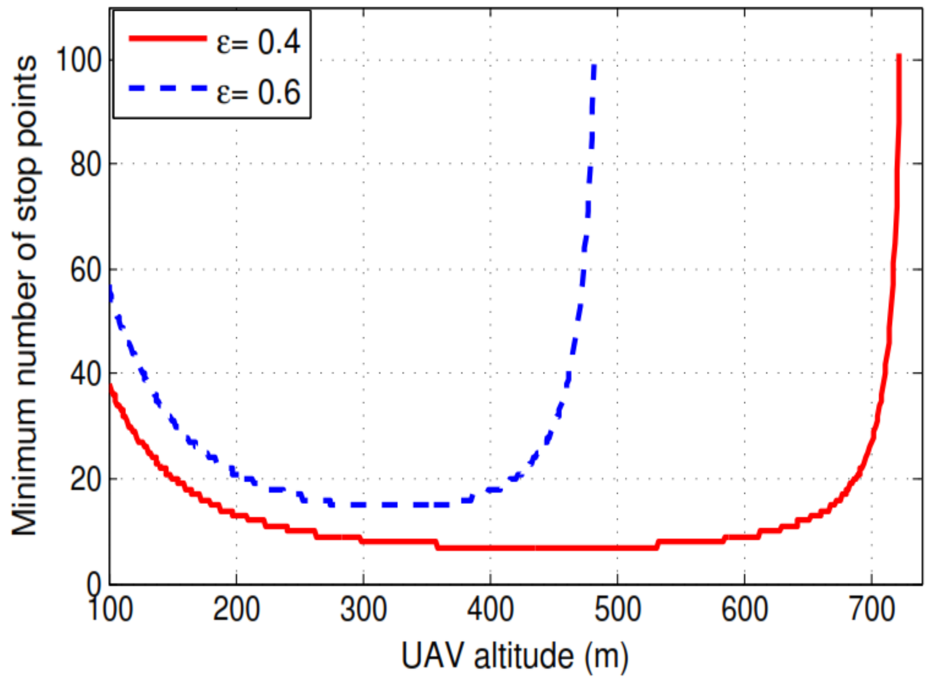
Results: Mobile UAV

- Number of stop points vs. D2D density
  - Higher number of D2Ds: higher interference
    - Increasing number of stop points!



Results: Mobile UAV

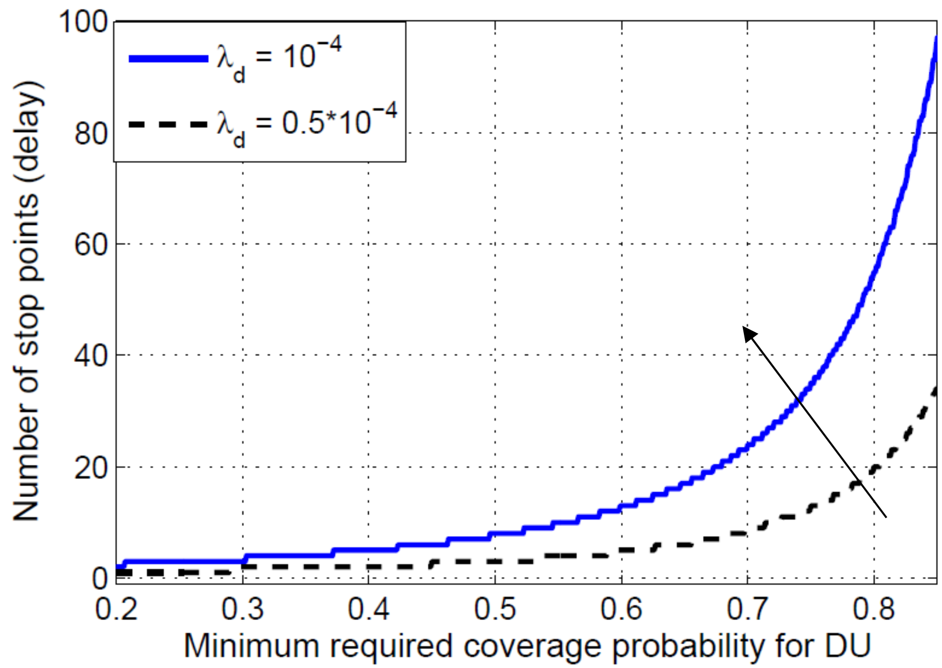
- Altitude and number of stop points
  - ϵ : target DU coverage requirement
  - Altitude impacts coverage range and thus number of stop points



Higher coverage requires more stopping points

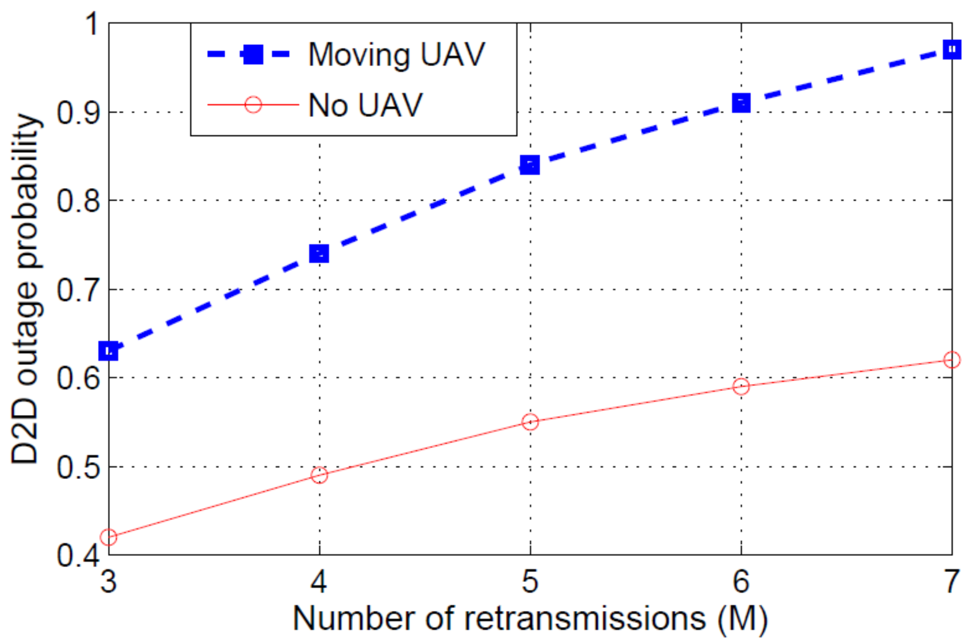
Results: Mobile UAV

- Coverage-delay tradeoff
  - Higher number of stop points:
    - Better coverage performance for DUs
    - Leads to a higher delay



Results: Mobile UAV

- UAV affects the D2D outage
  - No UAV: only other D2Ds create interference
  - With UAV: UAV+ other D2Ds are interference sources
    - Moving UAVs leads to higher average outage probability for D2D network



Part III – Optimal Deployment

Optimal Deployment and Mobility

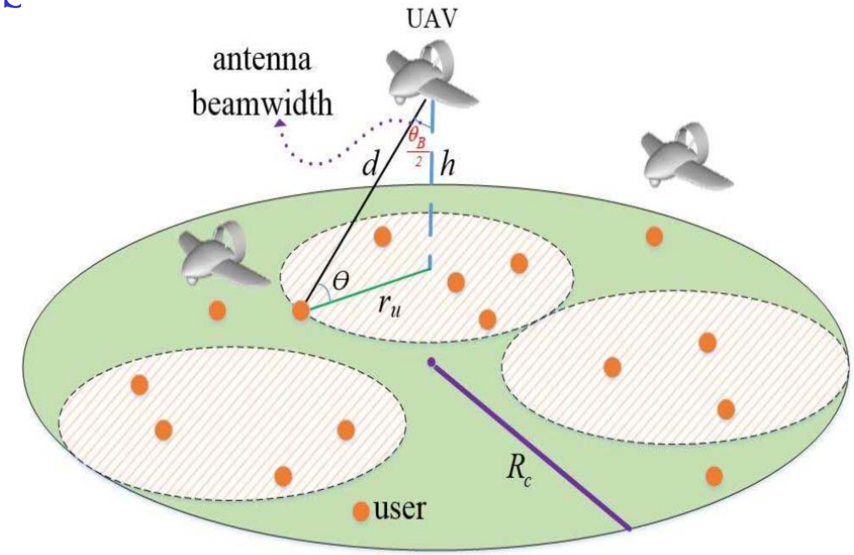
UAV Base Stations (LAPs)	Terrestrial Base Stations
• Deployment is **three-dimensional**	• Deployment is **two-dimensional** (with small exceptions)
• **Short-term, frequently changing** deployments	• **Mostly long-term, permanent** deployments
• Mostly **unrestricted locations**	• **Few, select** locations
• **Mobility** dimension	• **Fixed and static**

- **Where** and **when** to deploy UAV-BSs?
- What **metrics** to optimize (long term vs. short term)?
- How to develop **wireless-aware** path planning mechanisms?

Deployment strategies of multiple UAVs for optimal wireless coverage

System Model

- Downlink communications
- Using directional antennas for UAVs
- Interference between all UAVs
- Circular target area
- Meeting the minimum SINR requirement on the ground



Main Objectives

- Derive the coverage probability and coverage range of each UAV
- Maximize the coverage performance by efficient deployment of multiple UAVs
- Adjust UAVs' altitude based on antenna beamwidth
- Avoid overlapping coverage to avoid interference

Downlink Coverage Probability

- Considering shadowing effect in LoS and NLoS links

$$\psi_{\text{LoS}} \sim N(\mu_{\text{LoS}}, \sigma^2_{\text{LoS}}),\ \psi_{\text{NLoS}} \sim N(\mu_{\text{NLoS}}, \sigma^2_{\text{NLoS}})$$

$$P_{\text{cov}} = \mathbb{P}\left[P_r \geq P_{\text{min}}\right]$$

Q function

Received signal power

3 dB antenna gain

$$P_{\text{cov}} = P_{\text{LoS}} Q\left(\frac{P_{\text{min}} + L_{dB} - P_t - G_{dB} + \mu_{\text{LoS}}}{\sigma_{\text{LoS}}}\right) + (1 - P_{\text{LoS}})\, Q\left(\frac{P_{\text{min}} + L_{dB} - P_t - G_{dB} + \mu_{\text{NLoS}}}{\sigma_{\text{NLoS}}}\right)$$

Path loss

Multiple-UAVs deployment

- Coverage range of each UAV:

$$r_u = \max\{r | P_{\text{cov}}(r, P_t, \theta_B) \geq \varepsilon\}$$

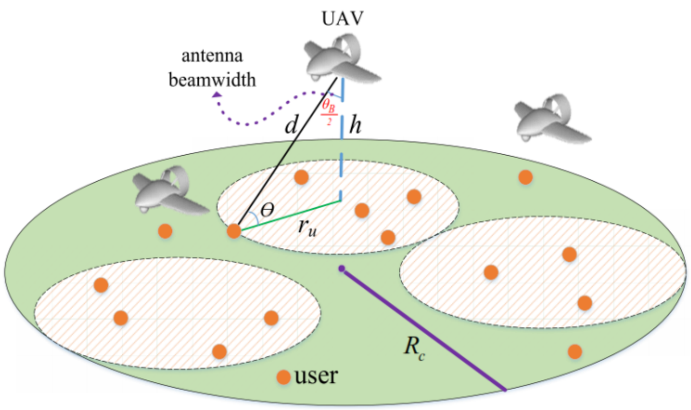
- *M* identical UAVs
- Total coverage is maximized
- No overlap between UAVs' coverage areas

$$(\vec{r_i}^*, h^*, r_u^*) = \underset{i \in \{1,\ldots,M\}}{\arg\max}\, M.r_u^2,$$

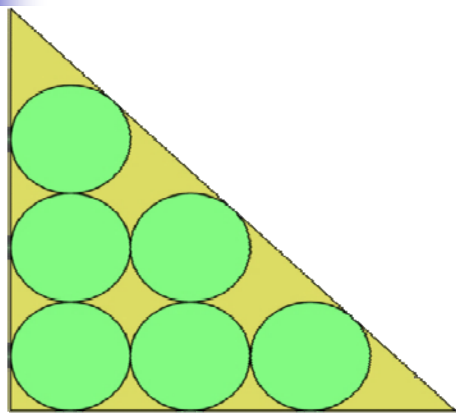
$$\text{st.} \;\; ||\vec{r}_j - \vec{r}_k|| \geq 2r_u, \;\; j \neq k \in \{1, ..., M\},$$

$$||\vec{r}_i + r_u|| \leq R_c,$$

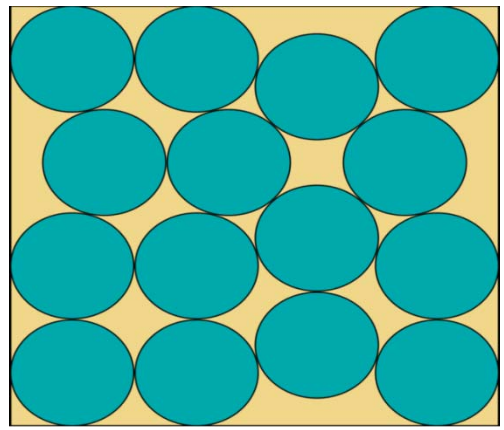
$$r_u \leq h.\tan(\theta_{\mathrm{B}}/2)$$



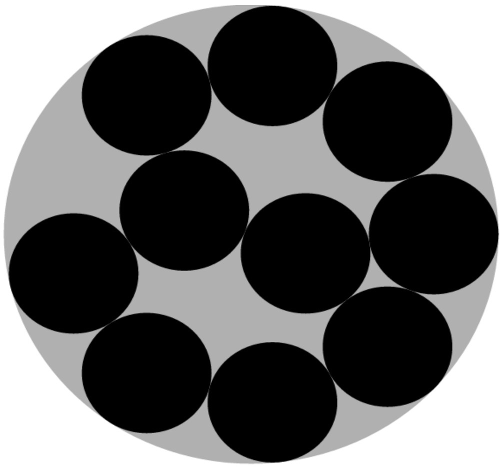
Approach: Circle Packing Problem



The optimal packing of 6 circles in a right isosceles triangle



The optimal packing of 15 circles in a square



The optimal packing of 10 circles in a circle

- Big circle: area of interest which needs to be covered
- Each small circle: Coverage region of each UAV

→Maximizing the packing density is equivalent to maximizing total coverage

Results

- Coverage radius vs. number of UAVs (circle packing):

Number of UAVs	Coverage radius of each UAV
1	R_c
2	$0.5R_c$
3	$0.464R_c$
4	$0.413R_c$
5	$0.370R_c$
6	$0.333R_c$
7	$0.333R_c$
8	$0.302R_c$
9	$0.275R_c$
10	$0.261R_c$

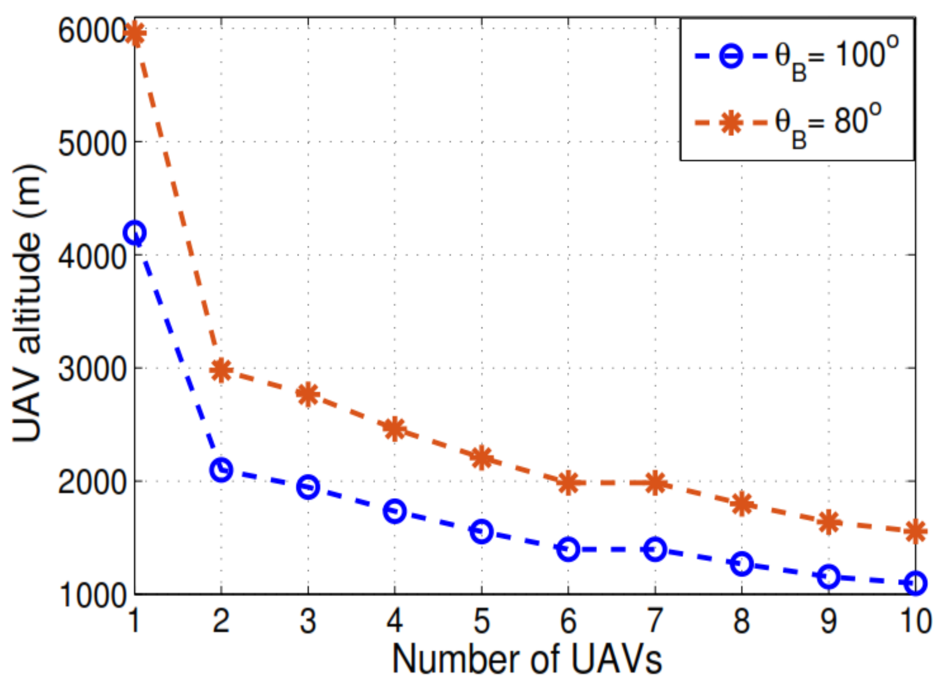
- Upper bound on the coverage radius:

$$r_u \leq \frac{q_m R_c}{(2+q_m)},$$

$$q_m = \max\left\{q \,\middle|\, \frac{\pi}{\sin^{-1}(q/2)}\left(\frac{q\sqrt{3}+\sqrt{4-q^2}}{q}\right) + \sqrt{12}(1-M) \geq 0\right\}$$

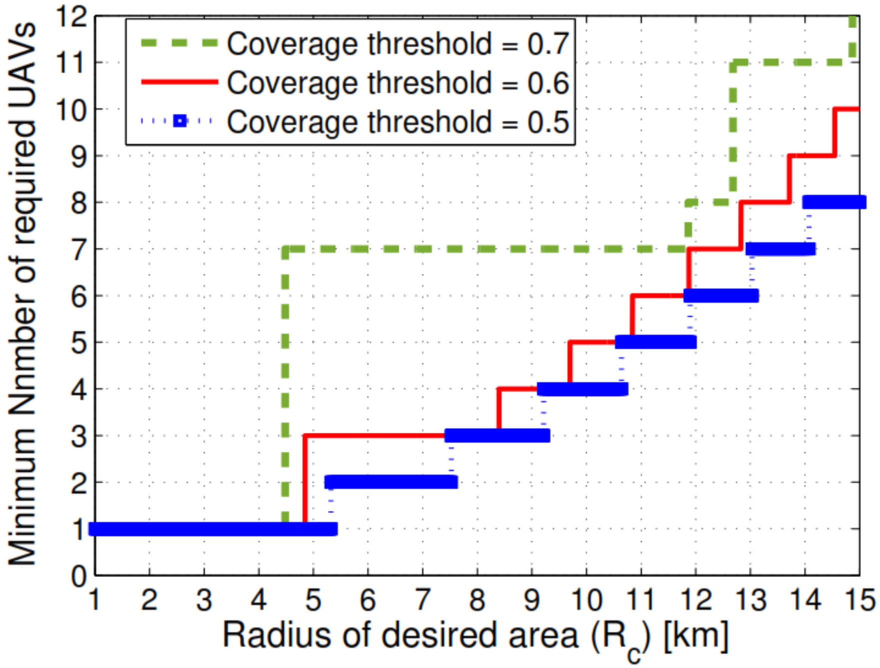
Results

- Altitude versus number of UAVs
- More UAVs:
  - Less coverage radius per UAV is required
  - Reduce UAVs' altitudes to avoid interference (overlapping)



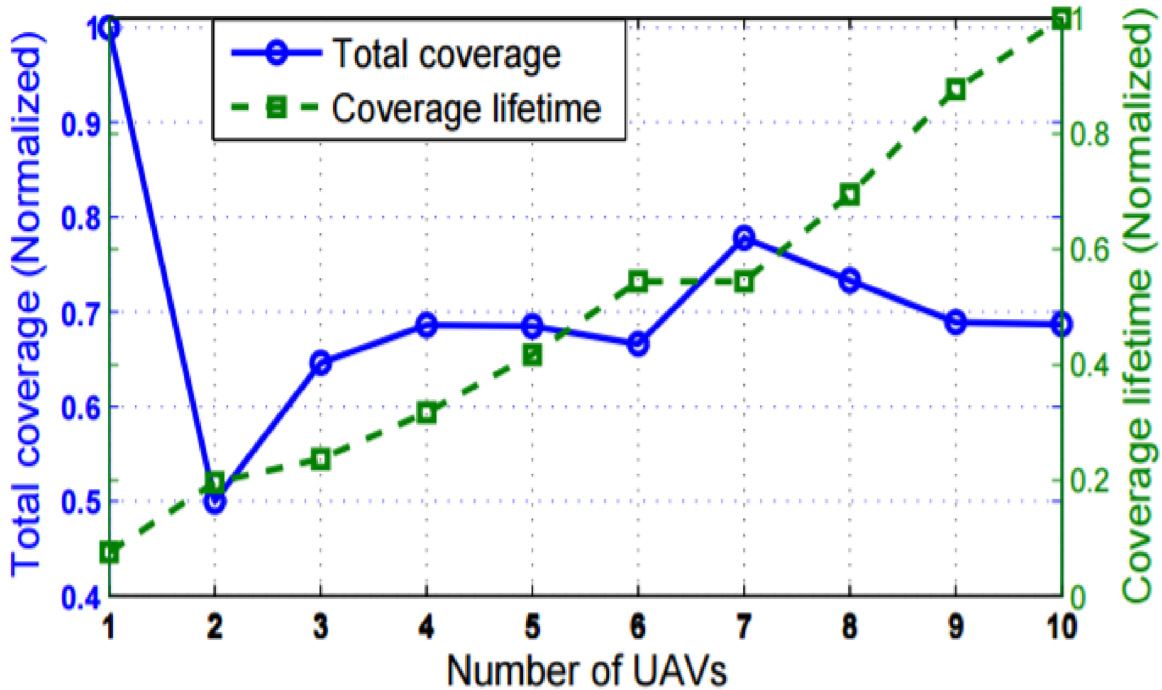
Results

- Meeting a total coverage requirement
  - What is the minimum number of UAVs?
  - Depends on the size of the area
  - Choosing appropriate number of UAVs based on coverage requirement and size of target area



Results

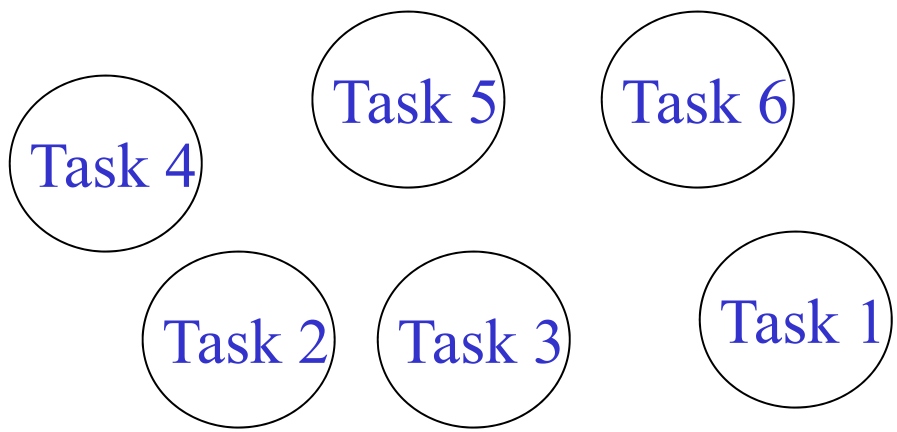
- Total coverage and coverage lifetime tradeoff
- Increasing number of UAVs:
  - Transmit power per UAV can be reduced
  - Higher coverage lifetime



Cooperative **deployment and mobility** of UAVs for optimizing rate-delay tradeoffs

Cooperative UAV Deployment

- Given a number of tasks in an area and some autonomous agents (e.g., UAVs)
  - How to dispatch the agents to service the tasks?
  - Can the agents make their own decisions on servicing the tasks?
  - Almost no work considered the problem in the context of a wireless/communication network
  - Tasks are **queues of data with no direct connectivity**



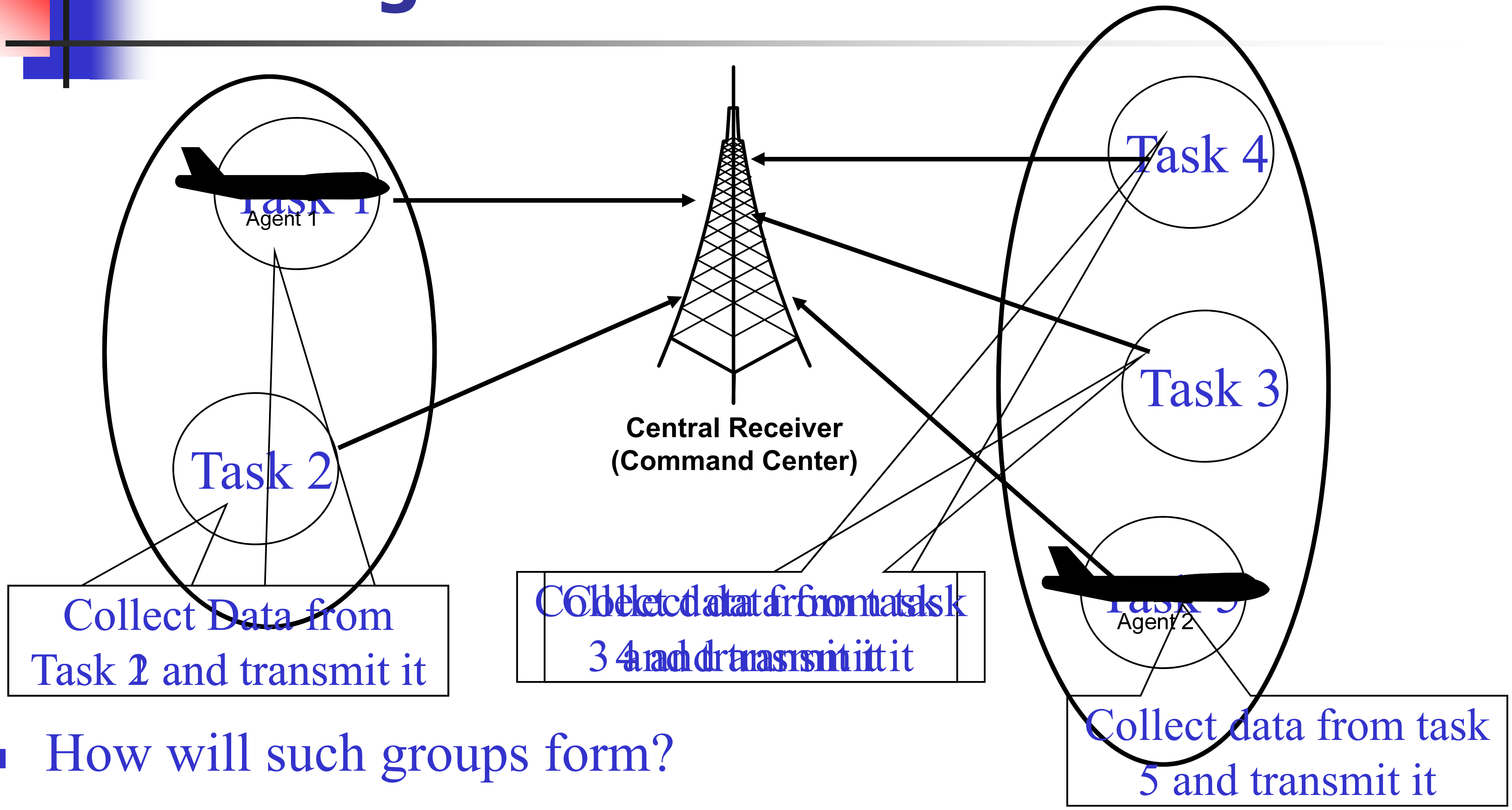
Cooperative UAV Deployment

- The problem is well studied but…
- Most approaches are
  - Robotics-oriented
  - Mainly in military applications (tasks are targets)
  - Other related problems (the repairman problem, dynamic vehicle problem…)
  - Software engineering (autonomous agents)
  - **The tasks are usually considered as passive entities**
- Almost no work considered the problem in the context of a wireless/communication network
  - With next generation self-organizing networks this problem becomes quite relevant
  - Nature of wireless networks (channel, traffic, etc)
  - Quality of service

Agents in Wireless Networks

- Given a number of tasks in an area
  - Consider each task as a M/D/1 queuing system generating packets with a Poisson arrival
  - Each task i has an arrival rate λ_i
- The network operator, requires..
  - Data collection from the tasks
  - Wireless transmission of the data to a central receiver
- The network owns a number of autonomous agents that need to
  - Decide on which tasks to service
  - Collect the data and transmit it taking into account
    - The amount of data collected
    - The delay

UAV Agents in Wireless Networks



- How will such groups form?
- A cooperative game between **Tasks and Agents**
  - Solution using notions from operations research, wireless networks, and queuing theory

Problem Formulation

- Coalitional game where
  - The players are **the tasks and UAVs**, hence, the player set N is the set of all tasks and UAVs
    - Denote M the set of UAVs and T the set of tasks, $N = M \cup T$
  - Each coalition S consists of a number UAVs servicing a number of tasks t
- A UAV can be either
  - A **collector:** more collectors means smaller service time, less delay
    - Each collector i has a link transmission capacity μ_i
    - For a number of collectors G servicing a task i in a coalition S the total link transmission capacity is

$$\mu_G^i = \sum_{j \in G} \mu_j$$

  - A **relay:** more relay means better effective throughput (less outage probability)

Problem Statement

- Each coalition *S* can be seen as a **polling system with exhaustive strategy and switchover times**
  - Polling systems are ubiquitous in computer systems
  - The main idea is that a server is servicing multiple queues (sequentially or not)
    - Exhaustive implies the server collects all the available data from a queue before moving to the next
  - Switchover times are the time to move from one task to the other
- In this context, each coalition *S* consists of
  - A number of collectors acting as the polling system server
  - The tasks are the queues of the polling system
  - Switchover time is the travel time from one task to the next

Performance metrics - Delay

- For a polling system, it is difficult to have an exact expression for delays, but, we can use the pseudo-conservation law for a coalition *S*

$$\sum_{i \in S \cap \mathcal{T}} \rho_i \bar{W}_i = \rho_S \frac{\sum_{i \in S \cap \mathcal{T}} \frac{\rho_i}{\mu^i_{S \cap \mathcal{M}}}}{2(1-\rho_S)} + \rho_S \frac{\theta_S^2}{2} + \frac{\theta_S}{2(1-\rho_S)} \left[\rho_S^2 - \sum_{i \in S \cap \mathcal{T}} \rho_i^2 \right]$$

Utilization factor ρ_i: ratio of arrival rate to link transmission capacity of collectors for a task *i*

Total switchover time θ_S of coalition *S*

Sum of utilization factors over all tasks in *S*

- Stability of coalition S (polling system) requires $\boldsymbol{\rho_S < 1}$
- The total switchover time θ_S depends on the sequence in which the tasks are visited
  - Nearest neighbor solution to the travelling salesman problem

Performance metrics - Throughput

- For each coalition, the total effective throughput from the data collected and transmitted is given by

$$L_S = \sum_{i \in S \cap \mathcal{T}} \lambda_i \cdot \mathrm{Pr}_{i,\mathrm{BS}}$$

  - $\mathrm{Pr}_{i,\mathrm{BS}}$ is the outage probability for wireless transmission from task *i* to the central BS
    - Improved by having UAVs working as relays on the link between the collectors on task *i* and the BS

- For each coalition, the UAVs and tasks are given a reward from the network operator depending on the throughput-delay trade off achieved

Utility function

- Given the throughput and delay previously defined, for each coalition *S* we propose the following utility

$$v(S) = \begin{cases} \delta \dfrac{L_S^{\beta}}{(\sum_{i \in S \cap \mathcal{T}} \rho_i \bar{W}_i)^{(1-\beta)}}, & \text{if } \rho_S < 1 \ \& \ |S| > 1 \\ 0, & \text{otherwise} \end{cases}$$

  - β is a tradeoff parameter that represents the weight that a coalition puts on the throughtput and delay
  - The utility is based on the concept of *power* which is a ratio between effective throughput and delay
  - Utility is transferable: the total **revenue** achieved by coalition S with δ the revenue per unit power
- Given the players set *N* and the utility *v* the question is
  - We use the framework of hedonic coalition formation games to solve the problem

Hedonic Coalition Formation

- In our game we can say that
- A **UAV** prefers a coalition S_1 over a coalition S_2 if
  - The UAV is not the **only** UAV in its current coalition S_2 **and**
  - The payoff he receives in S_1 is higher than S_2, and he had not visited this coalition before (history tracking).

$$S_2 \succeq_{\mathcal{M}} S_1 \Leftrightarrow u(S_2) \geq u(S_1)$$

$$u(S) = \begin{cases} \infty, & \text{if } S = S_{\Pi}(i) \ \& \ S \setminus \{i\} \subseteq \mathcal{T} \\ 0, & \text{if } S \in h(i) \\ x_i^S. & \text{otherwise} \end{cases}$$

  - x_i^S is the payoff received by player i from the division of the utility (we consider equal division for this work)
  - *h(i)* history set

Hedonic Coalition Formation

- A **task** prefers a coalition S_1 over a coalition S_2 if
  - The payoff he receives in S_1 is higher than S_2, and he had not visited this coalition before (history tracking).

$$S_2 \succeq_{\mathcal{T}} S_1 \Leftrightarrow w(S_2) \geq w(S_1)$$

$$w(S) = \begin{cases} 0, & \text{if } S \in h(i) \\ x_i^S, & \text{otherwise} \end{cases}$$

- By using these preferences we can derive an algorithm form coalitions between the UAVs and the tasks
- Having defined the preferences, the next question is
  - **How to form the coalitions?**

Coalition Formation Algorithm

- Coalitions form and break as a result of **selfish** decisions by the players (agents and tasks)
- Switch rule

$$\{S_m, S_k\} \rightarrow \{S_m \setminus \{i\}, S_k \cup \{i\}\}, \; i \in S_m$$

$$\text{if } S_k \cup \{i\} \succ_i S_{\Pi}(i).$$

  - Every player switches its current coalition to join another, if and only if the new coalition is *strictly* preferred using the defined preferences.

Coalition formation algorithm

Initial Network State:
Non-cooperative network

↓

Task discovery:
The central BS informs the UAVs of the tasks in the area

↓

Each player (UAV or task) surveys nearby coalitions for possible switch

↓

Each player takes the switch Decision that maximizes its payoff

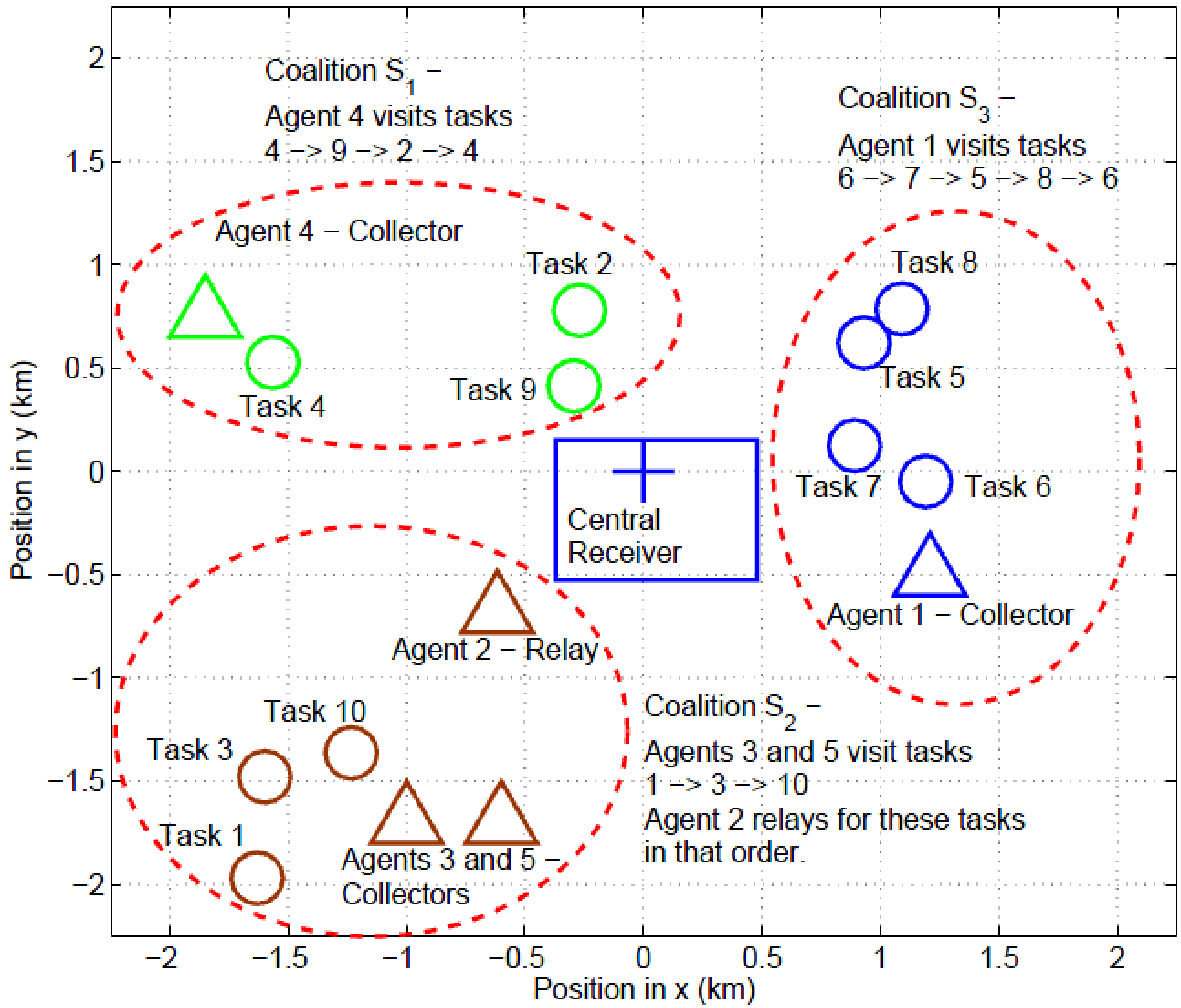
Sequential switch operations until convergence

↓

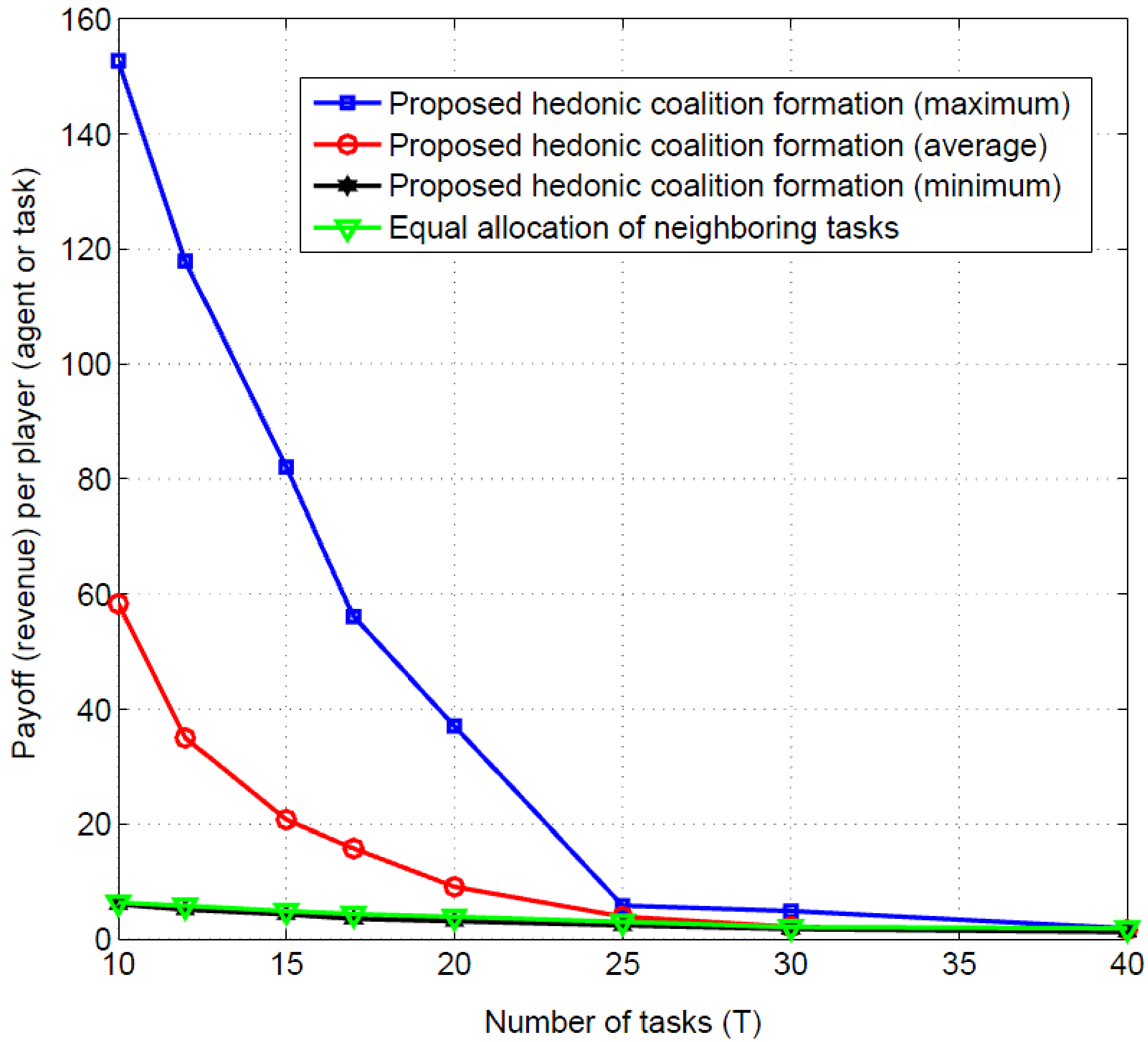
Final partition: Continuous data collection and transmission by the UAVs

The final partition is Nash-stable, no player has an incentive to unilaterally change its coalition

Simulation results (1)



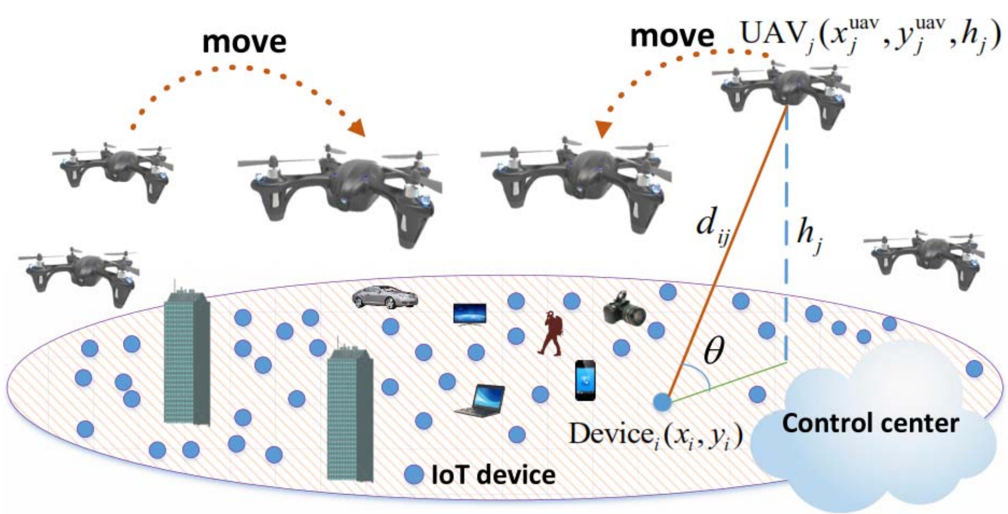
Simulation results (2)



Mobile UAVs for Energy-Efficient Internet of Things Communications

System Model

- Uplink IoT communications
- Meeting SINR requirements of IoT devices
- Periodic versus Probabilistic IoT activation models
- UAVs update their locations based on devices activation patterns



IoT devices

- Battery limited
  - Typically unable to transmit over a long distance due to their energy constraints
  - UAVs can dynamically move towards IoT devices, collect the IoT data → moving IoT aggregators
- Many IoT devices→interference issue
- IoT activations:
  - Periodic: weather monitoring and smart grids applications
  - Probabilistic: health monitoring and smart traffic control applications.

Main Objectives

- How to enable reliable and energy-efficient uplink communications in a large-scale IoT using UAVs?

- What are the joint optimal 3D UAVs' locations, device-UAV associations and uplink power control?

- Need for a framework for updating UAVs locations in time-varying networks:
  1) Update times: shows how frequently UAVs update their locations
  2) UAV trajectories

Problem Formulation

- Joint UAVs' locations, associations, and power optimization

IoT transmit power

Set of active IoT devices

$$\min_{\boldsymbol{v}_j, \boldsymbol{c}, \boldsymbol{P}} \sum_{i=1}^{L_n} P_i \,, \quad \forall i \in \mathcal{L}_n, \; \forall j \in \mathcal{K},$$

UAV j location

$$\text{s.t.} \quad \frac{P_i \bar{g}_{ic_i}(\boldsymbol{v}_{c_i})}{\sum_{k \in \mathcal{Z}_i} P_k \bar{g}_{kc_i}(\boldsymbol{v}_{c_i}) + \sigma^2} \geq \gamma,$$

SINR Constraint

Association matrix

$$0 < P_i \leq P_{\max},$$

Channel gain

General Approach

- Decompose the problem into two subproblems
  - Solve the problem for fixed association
  - Solve the problem for fixed UAVs' locations

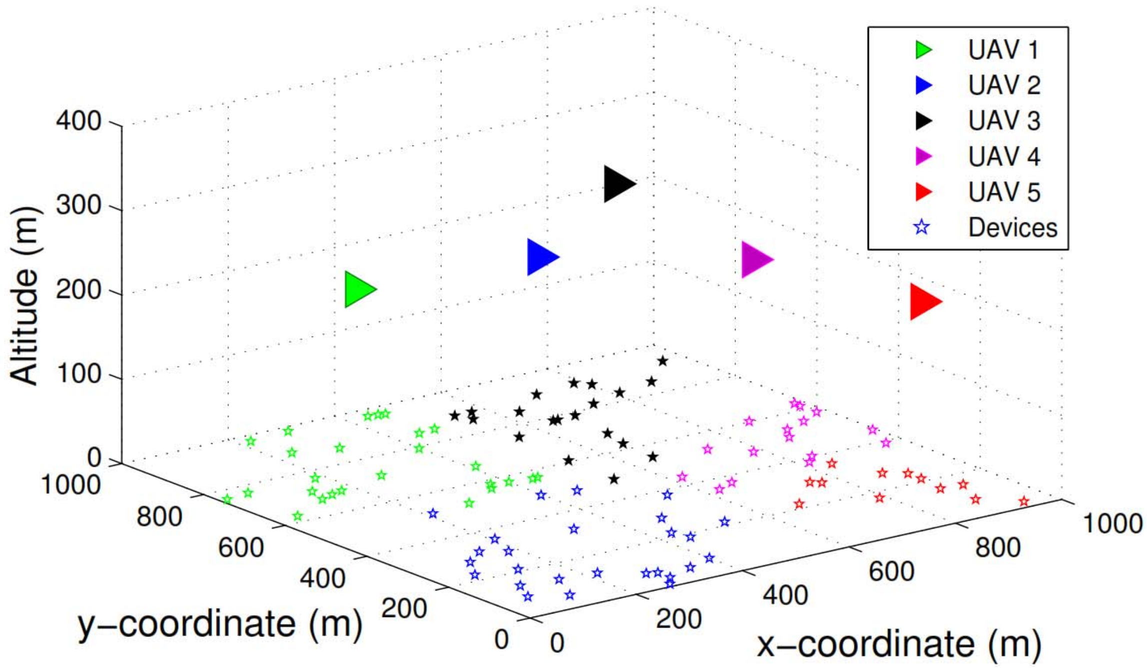
$$\min_{\boldsymbol{c},\boldsymbol{P}} \sum_{i=1}^{L_n} P_i\,, \quad \forall i \in \mathcal{L}_n,\ \forall j \in \mathcal{K},$$
$$\text{s.t. } \frac{P_i \bar{g}_{ic_i}}{\sum\limits_{k\in\mathcal{Z}_i} P_k \bar{g}_{kc_i} + \sigma^2} \geq \gamma,$$
$$0 < P_i \leq P_{\max}.$$

$$\min_{\boldsymbol{v}_j,\boldsymbol{P}} \sum_{i=1}^{L_n} P_i\,, \quad \forall i \in \mathcal{L}_n,\ \forall j \in \mathcal{K}$$
$$\text{s.t. } \frac{P_i \bar{g}_{ij}(\boldsymbol{v}_j)}{\sum\limits_{k\in\mathcal{Z}_i} P_k \bar{g}_{kj}(\boldsymbol{v}_j) + \sigma^2} \geq \gamma,$$
$$0 < P_i \leq P_{\max},$$

  - Consider interference and non-interference scenarios separately

Results

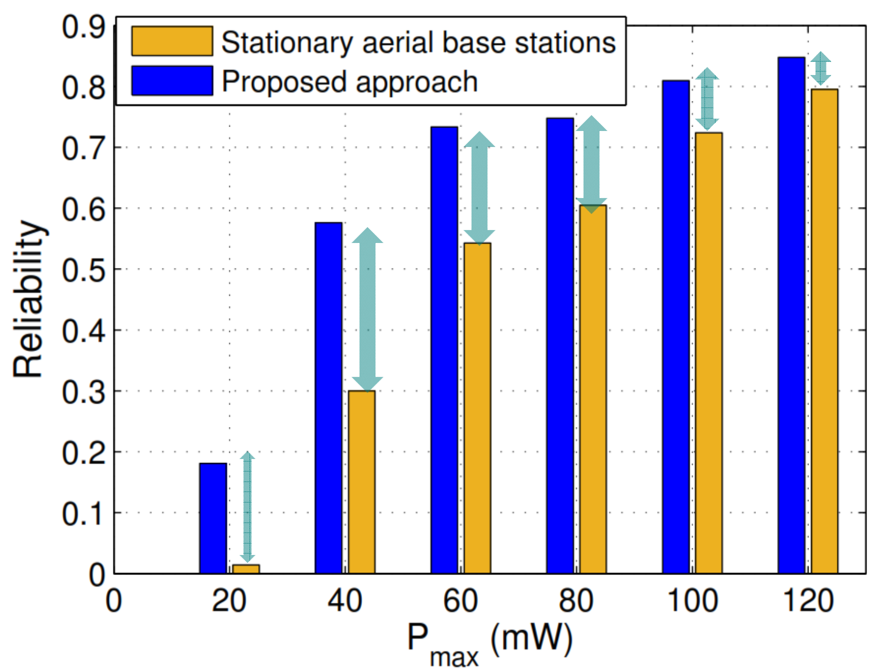
- UAVs' locations and device-UAV association
  - An example, given the locations of active IoT devices



❖ 5 UAVs serving 100 active IoT devices uniformly distributed over the area

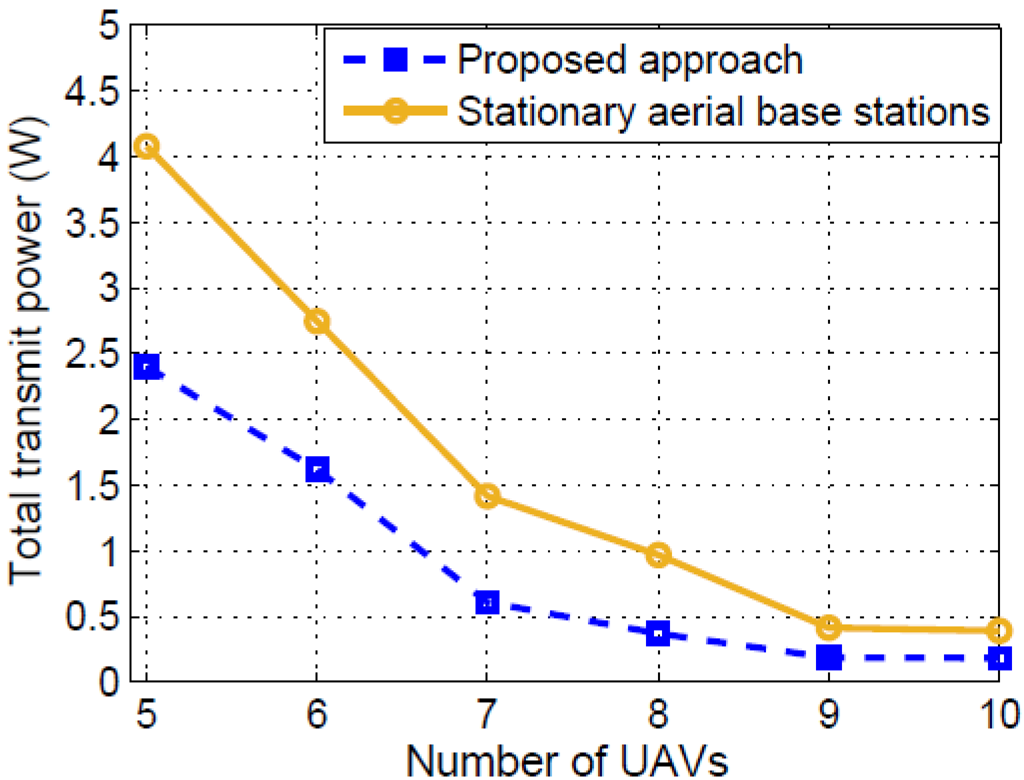
Results

- Reliability
  - Probability that active devices are successfully served by UAVs
  - Significant enhancement by dynamically moving UAVs



Results

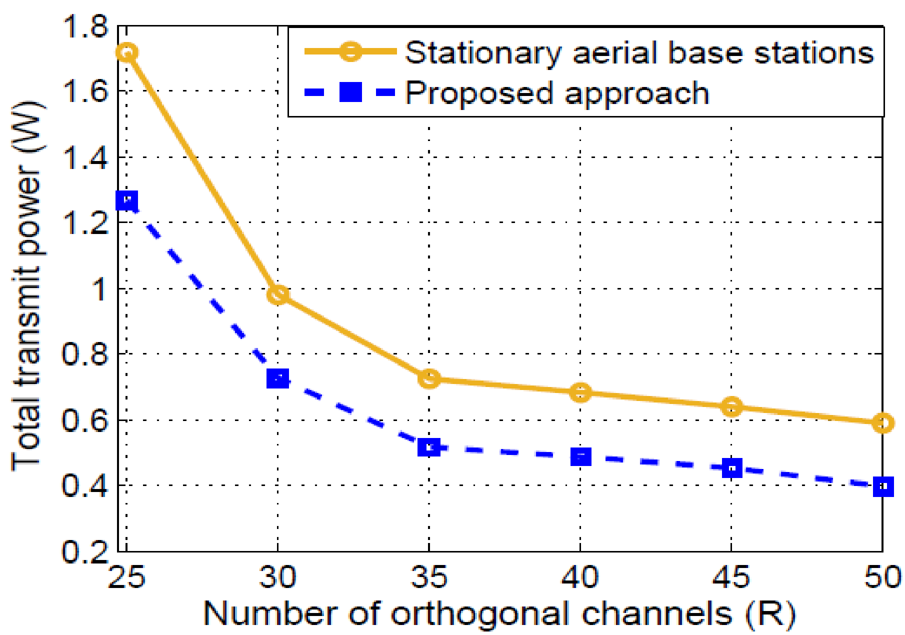
- Total transmit power vs. number of UAVs
  - Compared with stationary aerial base stations



- 5% power reduction vs. baseline on the average

Results

- Total transmit power vs. number of orthogonal channels for meeting SINR requirements
  - More channels:
    - less interference and hence, lower transmit power needed to meet SINR requirements of each device

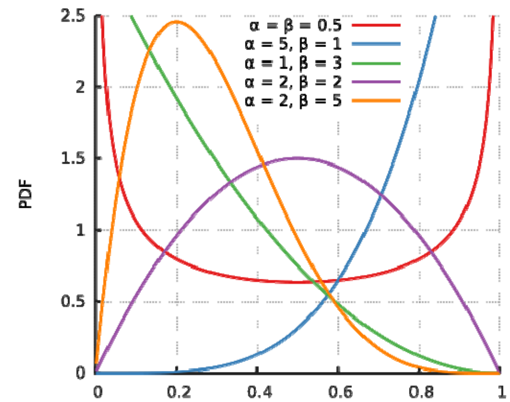


- 100 devices served by 5 UAVs
- By increasing the number of channels from 25 to 50, the total transmit power of devices can be reduced by 68%

IoT activation models

- Time varying IoT network
- UAVs dynamically update their locations based on IoT activations
- Probabilistic activation during [0,*T*]:

$$f(t) = \frac{t^{\kappa-1}(T-t)^{\omega-1}}{T^{\kappa+\omega-1}B(\kappa,\omega)}$$



where $\mathrm{B}(\alpha,\beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$

  - Beta distribution with parameters κ, ω
- Periodic activation:
  - Each device has a specific activation period

UAVs’ update times

- Time instance at which the UAVs’ locations and associations are updated
- Depends on the activation process of IoT devices
- Number of IoT devices
  - For higher number of devices more updates are needed!
- Energy of the UAVs
  - More updates requires more mobility

UAVs' update times

- For probabilistic activation case
- Choosing appropriate update times based on number of active devices

Regularized incomplete beta function

$$t_n = T \times I^{-1}\left(\frac{a_n}{L} + I_{\frac{t_{n-1}}{T}}(\kappa, \omega), \kappa, \omega\right), \; n > 1,$$

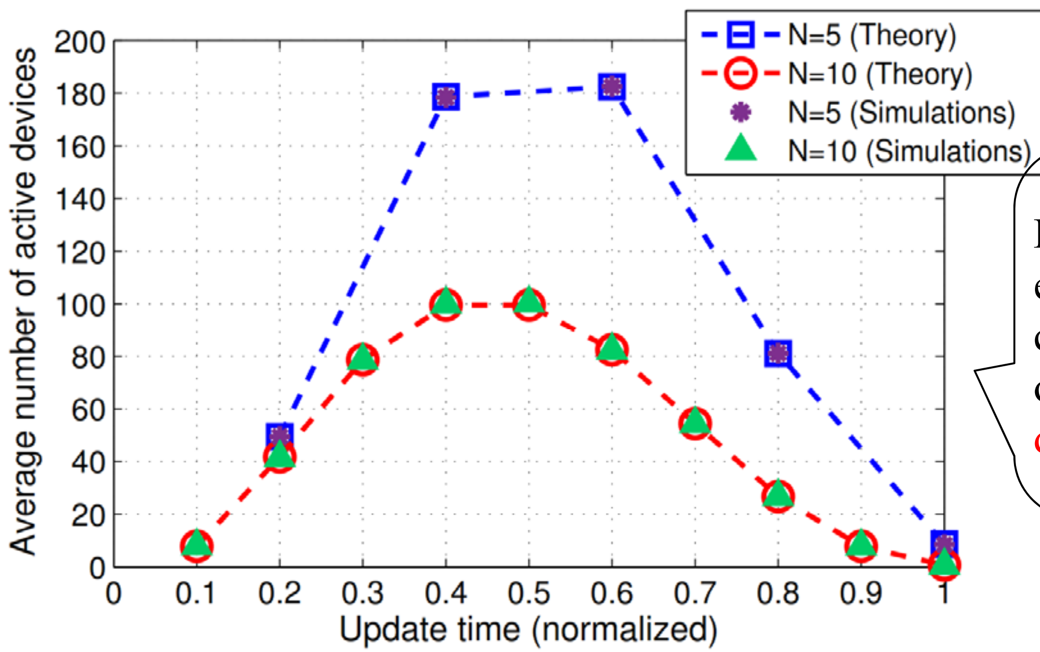
$$t_1 = T \times I^{-1}\left(\frac{a_1}{L}, \kappa, \omega\right),$$

Average number of active devices

Total number of devices

Results

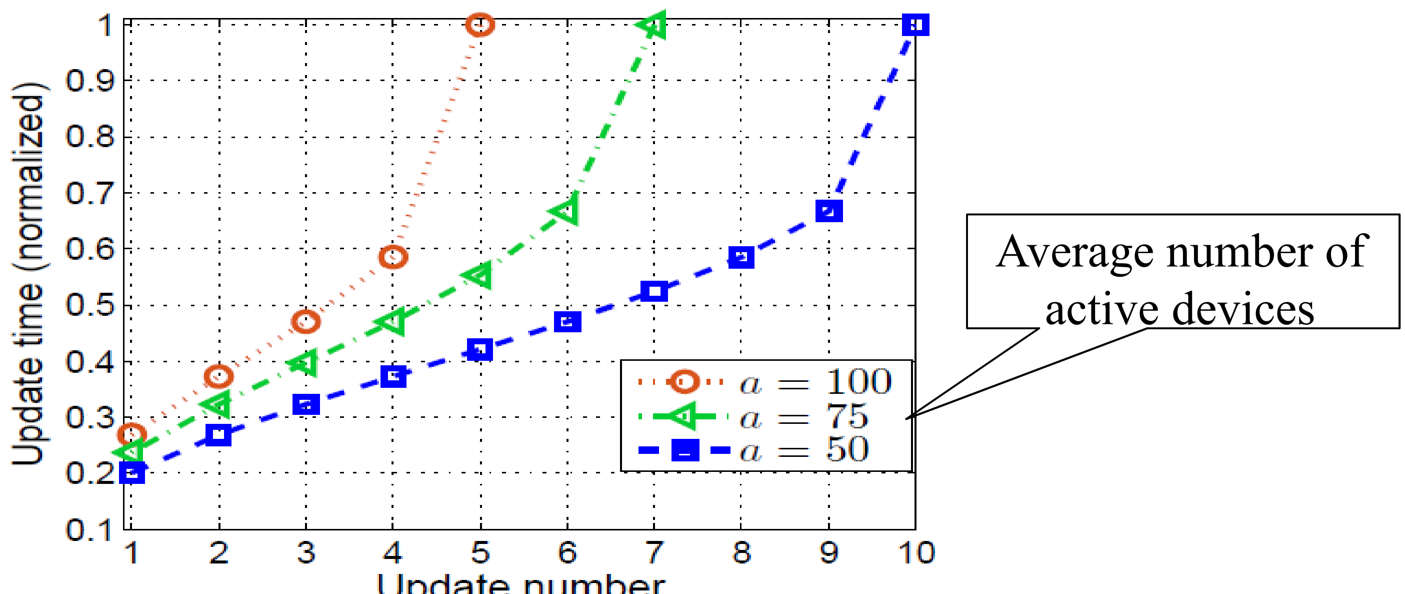
- Number of devices which must be served vs. update time
- More frequent updates:
  - More devices can be served
  - Less active (unserved) devices remain



For a higher number of update times or equivalently shorter time period between consecutive updates, the average number of devices that need to transmit their data decreases

Results

- Update times for different number of active devices
  - Depends on the activation process (beta distribution parameters)
  - Ensuring that the average number of active devices is less than *a*



- To achieve lower value of *a*, updates need to be done more frequently so as the time interval between updates decreases.
- For e.g., to meet *a* = 100, 75, and 50, the 5th update must occur at t = 0.41, 0.55, and 1

UAVs' mobility

- UAVs update their locations according to the activity of the IoT devices
- How to optimally move UAVs between the initial and the new sets of locations?
  - Mobility with minimum total energy consumption
  - Energy consumption of each UAV depends on travel distance, UAV's speed and power consumption as function of speed

$$E(D,v) = \int_{t=0}^{t=D/v} p(v)\mathrm{d}t = \frac{p(v)}{v}D$$

Travel time

UAVs' mobility

- Which UAV goes where?

Can be transformed into an ***assignment problem***

Transportation matrix

$$\min_{Z} \sum_{l\in\mathcal{I}_n} \sum_{k\in\mathcal{I}_{n-1}} E_{kl} Z_{kl}$$

Energy from location k to l

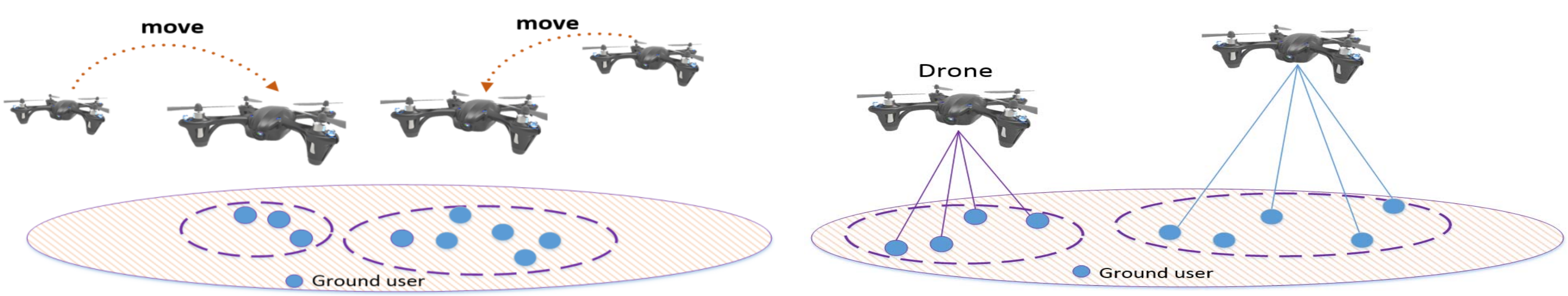
Initial set of UAVs' locations

New set of UAVs' locations

$$\text{s.t.} \sum_{l\in\mathcal{I}_n} Z_{kl} = 1, \quad \sum_{k\in\mathcal{I}_{n-1}} Z_{kl} = 1,$$

$$E_{lk} \le \Gamma_{n,k}\,, \quad Z_{kl} \in \{0,1\}, \ \forall k \in \mathcal{I}_{n-1}, \ \forall l \in \mathcal{I}_n$$

Energy constraint of each UAV

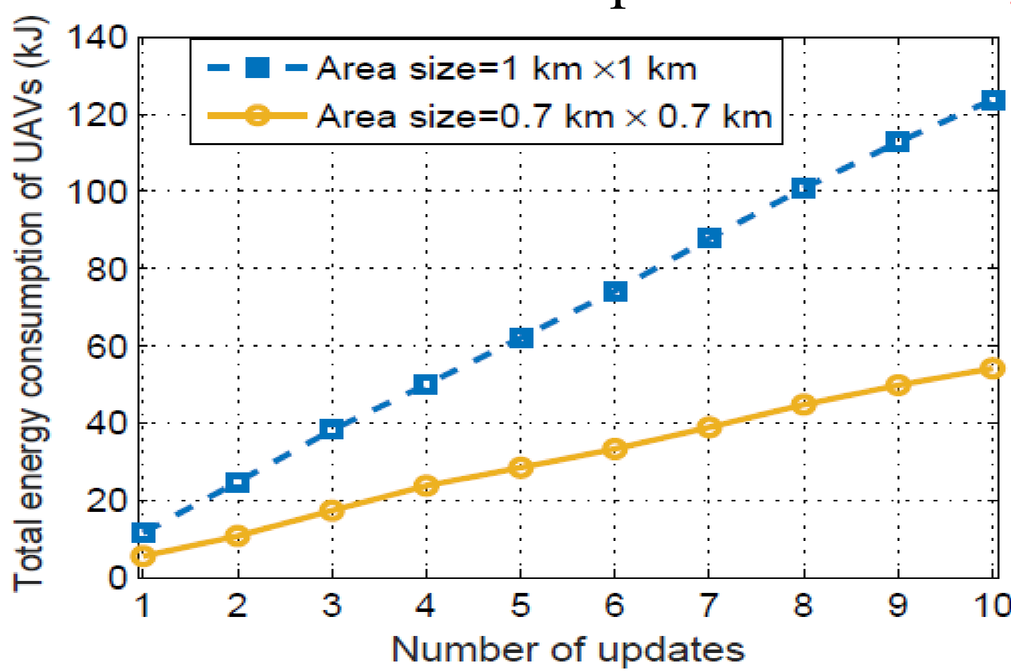


Update time t_2

Update time t_1

Results

- Update times impact the UAVs' energy consumption for mobility
  - More updates→UAVs need to spend more energy on mobility



- by increasing the number of updates from 3 to 6, the energy consumption of UAVs increases by factor of 1.9

Part IV – Resource Management

Resource management

UAV Networks	Terrestrial Networks
• Spectrum is scarce	• Spectrum is scarce
• **Inherent ability for LoS** communication can facilitate high-frequency (mmW)	• **Difficulty to maintain LoS** poses challenges at high frequencies
• **Elaborate and stringent** energy constraints and models	• **Well-defined** energy constraints and models
• **Varying** cell association	• **Static** association
• **Hover and flight time constraints**	• No timing constraints, BS always there

- Let's first take a look on the impact of hover time

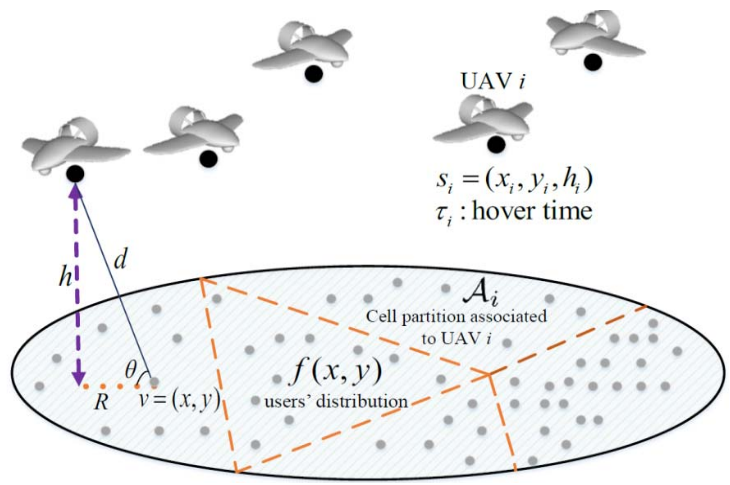
Optimal Transport Theory for Hover Time Optimization

Flight Time Constraints?

- UAVs have limited on-board batteries
  - Cannot fly for a long time
- Flight regulations and weather conditions
  - No-fly time and no-fly zones
  - Wind and rain effects
- Mobility based on demands
  - Cannot stay at one location for a long time

- Flight time constraints must be taken into account:
  - Minimizing flight time while meeting the demands
  - Optimizing the service performance under flight time constraints

System Model



- M stationary UAVs serve N users
- Users' distribution: $f(x, y)$
  - 2D spatial distribution of users
  - Determines how likely a user is present
- M partitions each serviced by one UAV
- **Hover time:** Time duration that a UAV spends over a given area
- Channel model adopted is the one explained earlire
- Goal: finding optimal cell partitions and associations
  - Based on users' distribution, hover times, and UAVs' locations
- Two scenarios:
  - Maximizing total service data given the maximum hover times (Scenario 1)
  - Minimizing average hover time while meeting load requirements (Scenario 2)

Problem Formulation (Scenario 1)

- Total bandwidth for UAV *i* : B_i
- Hover time of UAV *i* : τ_i
- Effective data transmission time: T_i
- Control time which is not used for transmission: $g_i = \tau_i - T_i$
  - Portion of hover time which is not used for data transmission
  - Used for processing, computations, and control signaling.
  - Is a function of the average number of users
- Data transmitted to a user located at *(x,y)* served by UAV *i* :

$$L_i(x, y) = T_i W_i \log_2 \left(1 + \gamma_i(x, y)\right),$$

Data (in bits)

SINR

$$W_i = \frac{B_i}{\underbrace{N \int_{\mathcal{A}_i} f(x, y) \mathrm{d}x \mathrm{d}y}_{\text{Average number of users in } \mathcal{A}_i}}$$

Bandwidth per user (average) assuming equal allocation

Scenario 1

- Time and bandwidth are the resources
- We consider some level of fairness in resource allocation:

$$T_i W_i = \frac{\alpha_i}{\alpha_j} T_j W_j \,, \quad \forall i \neq j \in \mathcal{M},$$

$\frac{\alpha_i}{\alpha_j}$: resource allocation factor

- Maximizing average total data service by optimal partitioning:

Finding optimal partitions is challenging

$$\max_{\mathcal{A}_i, i \in \mathcal{M}} \sum_{i=1}^{M} \int_{\mathcal{A}_i} L_i(x,y) f(x,y) \mathrm{d}x \mathrm{d}y, \tag{1}$$

Depends on hover times and bandwidths

$$\text{s.t.} \int_{\mathcal{A}_i} f(x,y) \mathrm{d}x \mathrm{d}y = \frac{\alpha_i B_i T_i}{\sum_{k=1}^{M} \alpha_k B_k T_k}, \quad \forall i \in \mathcal{M}, \tag{2}$$

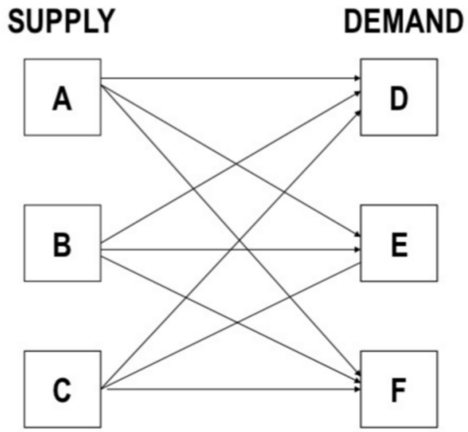
$$\gamma_i(x,y) \geq \gamma_{th}, \text{ if } (x,y) \in \mathcal{A}_i, \ \forall i \in \mathcal{M}, \tag{3}$$

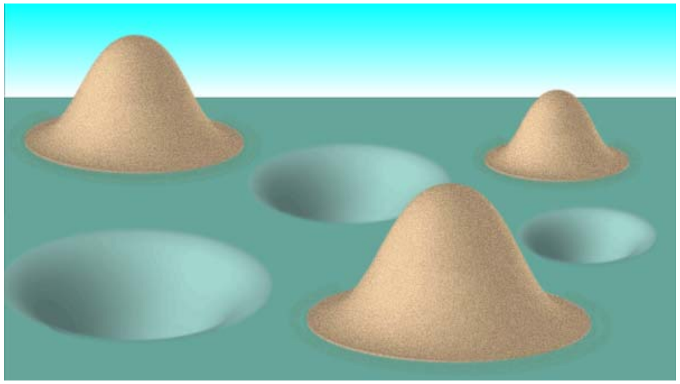
$$\mathcal{A}_l \cap \mathcal{A}_m = \emptyset, \ \forall l \neq m \in \mathcal{M}, \tag{4}$$

$$\bigcup_{i \in \mathcal{M}} \mathcal{A}_i = \mathcal{D}, \ \mathcal{A}_i \neq \emptyset, \forall i \in \mathcal{A}_i \tag{5}$$

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 users to UAVs!***

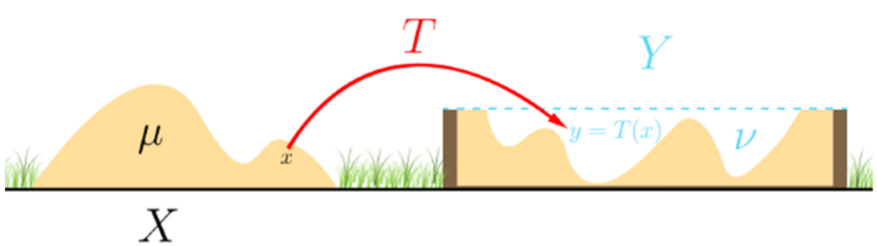
Monge-Kantorovich Transport Problem

- Given two probability distributions μ, 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 ?

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



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

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

Back to our problem

- We have a semi-discrete optimal transport problem
- Mapping from users' distribution (continuous) to UAVs (discrete)

$\boldsymbol{v}:(x,y)$ is user's location

$\boldsymbol{s}_i$ is 3D location of UAV i

- Optimal cell partitions are related to optimal transport maps

$$\left\{T(\boldsymbol{v})=\sum_{i\in\mathcal{M}}\boldsymbol{s}_i\mathbb{1}_{\mathcal{A}_i}(\boldsymbol{v});\int_{\mathcal{A}_i}f(x,y)\mathrm{d}x\mathrm{d}y=\omega_i\right\}$$

$$\mathbb{1}_{\mathcal{A}_i}(\boldsymbol{v})=\begin{cases}1, & \text{if } \boldsymbol{v}\in\mathcal{A}_i,\\ 0, & \text{if } \boldsymbol{v}\notin\mathcal{A}_i,\end{cases}$$

$$\boldsymbol{\omega_i}=\frac{\boldsymbol{\alpha_i B_i T_i}}{\sum\limits_{k=1}^{M}\boldsymbol{\alpha_k B_k T_k}}$$

Finding Optimal Partitions and Associations

Kantorovich Duality Theorem:

$$\min_{T} \int_X c\,(\boldsymbol{x}, T(\boldsymbol{x}))\mu(\boldsymbol{x})\mathrm{d}\boldsymbol{x} =$$

$$\max_{\varphi,\psi} \left\{ \int_X \varphi(\boldsymbol{x})\mu(\boldsymbol{x})\mathrm{d}\boldsymbol{x} + \int_Y \psi(\boldsymbol{y})v(\boldsymbol{y})\mathrm{d}\boldsymbol{y}\,;\, \varphi(\boldsymbol{x}) + \psi(\boldsymbol{y}) \le c(\boldsymbol{x},\boldsymbol{y}),\, \forall(\boldsymbol{x},\boldsymbol{y}) \in X \times Y \right\}$$

Theorem 1:

$$\max_{\psi_i, i\in\mathcal{M}} \left\{ F(\boldsymbol{\psi}^T) = \sum_{i=1}^{M} \psi_i \omega_i + \int_{\mathcal{D}} \psi^c(x,y) f(x,y)\mathrm{d}x\mathrm{d}y \right\},$$

where $\psi^c(x,y) = \inf_i J(x,y,\boldsymbol{s}_i) - \psi_i.$

Cost function depending on data service

- Finding optimal values of $\boldsymbol{\psi_i}$ leads to the optimal transport map and optimal cell partitions!
- Complete characterization of partitions is now possible

Finding Optimal Partitions and Associations

Theorem 2:

1) F is a concave function of $\psi_i, \ \forall i \in \mathcal{M}$

2) Using gradient based method to find optimal $\psi_i, \ \forall i \in \mathcal{M}$

3) Optimal cell partitions are given by:

$$\mathcal{A}_i = \left\{(x,y) | J(x,y,\boldsymbol{s}_i) - \psi_i^* \leq J(x,y,\boldsymbol{s}_j) - \psi_j^*, \forall j \neq i\right\}, \forall i \in \mathcal{M}$$

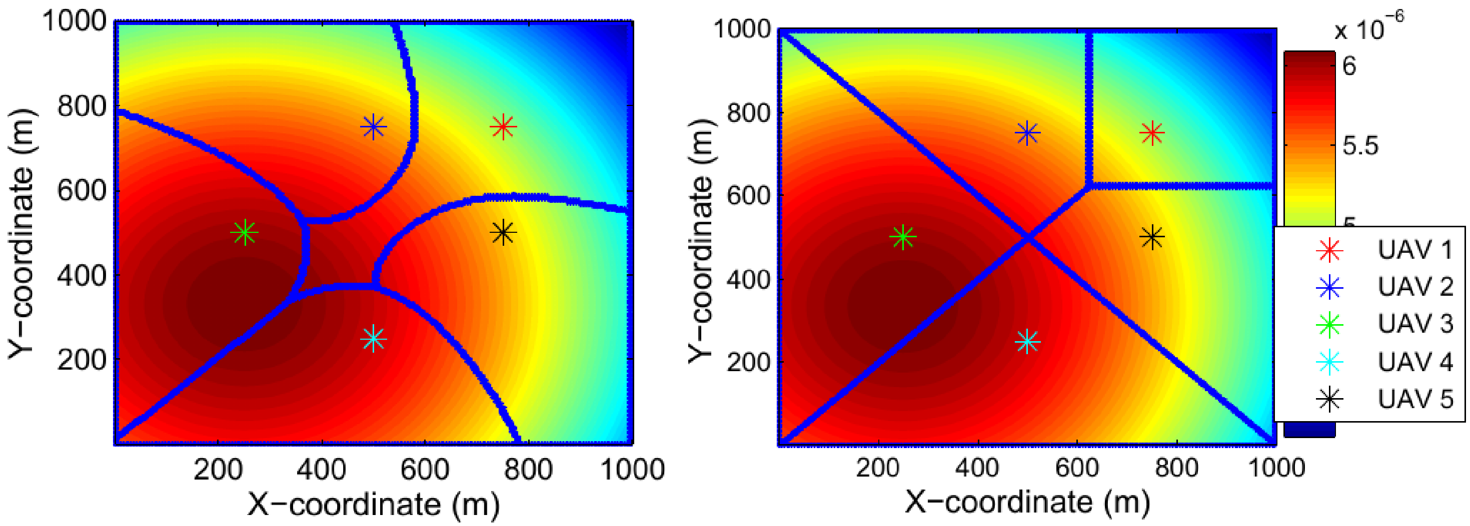
Special case: results in a weighted Voronoi diagram

Results: Scenario 1

- We consider truncated Gaussian distribution for users
  - Suitable for modeling hot spots in which users are congested

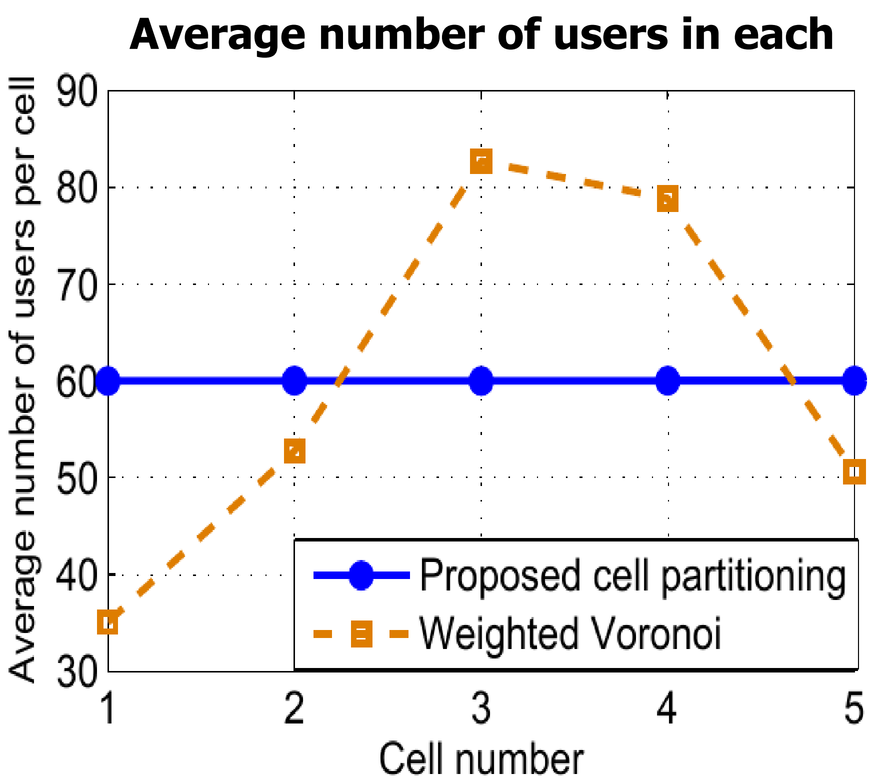
$$f(x,y) = \frac{1}{\eta}\exp\Big[-\Big(\frac{x-\mu_x}{\sqrt{2}\sigma_x}\Big)^2\Big]\exp\Big[-\Big(\frac{y-\mu_y}{\sqrt{2}\sigma_y}\Big)^2\Big]$$

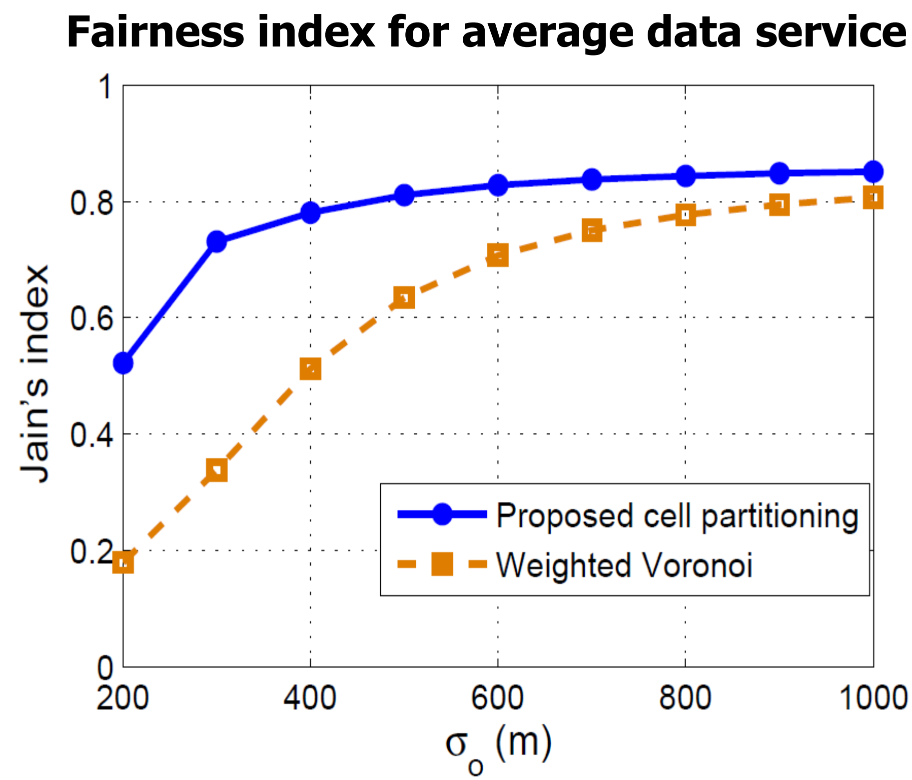
$$\eta \;=\; 2\pi\sigma_x\sigma_y \mathrm{erf}\left(\frac{L_x-\mu_x}{\sqrt{2}\sigma_x}\right)\mathrm{erf}\left(\frac{L_y-\mu_y}{\sqrt{2}\sigma_y}\right)$$



(a) Proposed optimal cell partitions. (b) Weighted Voronoi diagram.

Results: Scenario 1

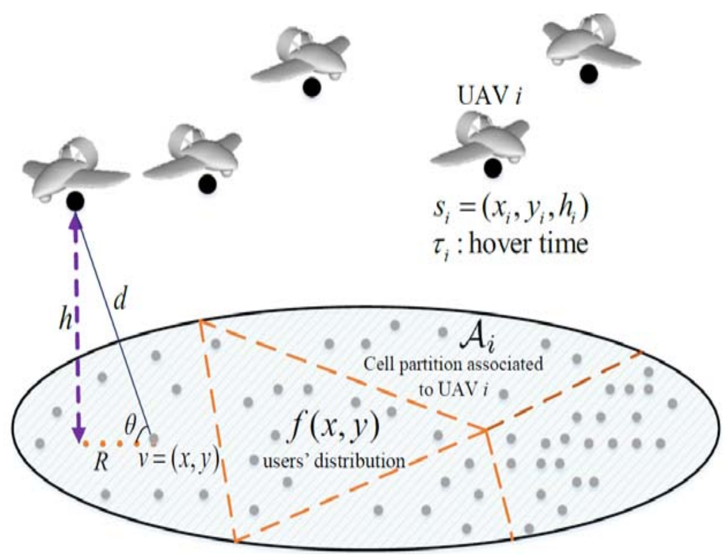




- Lower σ_o : users' distribution is more non-uniform
- Jain's fairness index is one when all users receive equal service

Scenario 2

- UAV-based communications under load constraints
- **Goal:** minimizing the average hover time needed for serving the users
- By finding optimal cell partitions



Average hover time of UAV i to service partition : $\mathcal{A}_i$

$C_i^{B_i}$: rate

Load (in bits)

$$\tau_i = \underbrace{\int_{\mathcal{A}_i} \frac{N u(x,y)}{C_i^{B_i}(x,y)} f(x,y)\mathrm{d}x\mathrm{d}y}_{\text{Transmission time}} + \underbrace{g_i\left(\int_{\mathcal{A}_i} f(x,y)\mathrm{d}x\mathrm{d}y\right)}_{\text{Control time}}$$

Problem Formulation (Scenario 2)

- Average total hover time of UAVs:

$$\min_{\mathcal{A}_i,\, i\in\mathcal{M}} \sum_{i=1}^{M} \int_{\mathcal{A}_i} \frac{Nu(x,y)}{C_i^{B_i}(x,y)} f(x,y)\mathrm{d}x\mathrm{d}y + g_i\left(\int_{\mathcal{A}_i} f(x,y)\mathrm{d}x\mathrm{d}y\right),$$

$$\text{s.t.}\quad \gamma_i(x,y) \geq \gamma_{\text{th}}, \ \ \text{if } (x,y)\in\mathcal{A}_i, \ \ \forall i\in\mathcal{M},$$

$$\mathcal{A}_l \cap \mathcal{A}_m = \emptyset, \ \ \forall l \neq m \in \mathcal{M},$$

$$\bigcup_{i\in\mathcal{M}} \mathcal{A}_i = \mathcal{D},$$

- We will characterize the optimal solution using optimal transport theory again

Optimal Partitions

Theorem 3: optimal cell partitions can be characterized as

$$\mathcal{A}_i^* = \left\{ (x,y) \middle| \frac{Nu(x,y)}{C_i^{B_i}(x,y)} + g_i'(a_i) \leq \frac{Nu(x,y)}{C_j^{B_j}(x,y)} + g_j'(a_j), \forall j \neq i \in \mathcal{M} \right\},$$

where $a_i = \int_{\mathcal{A}_i} f(x,y)\mathrm{d}x\mathrm{d}y$, and N is the total number of users.

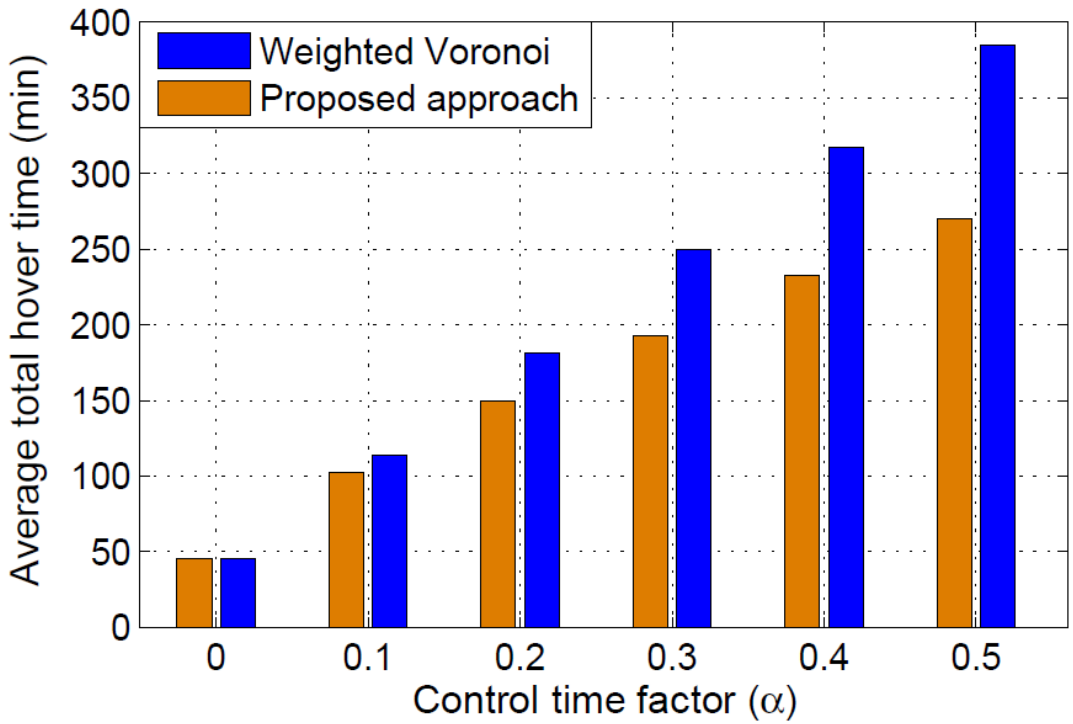
$$g_i{}'(a_i) = \left. \frac{dg_i(z)}{dz} \right|_{z=a_i}$$

- Proof idea:
  - Proving the existence of solution
  - Comparing optimal partitions and a non-optimal variation of those
  - Then characterizing the solution
- **Note:** weighted Voronoi is a special case (with no control time)

Results: Scenario 2

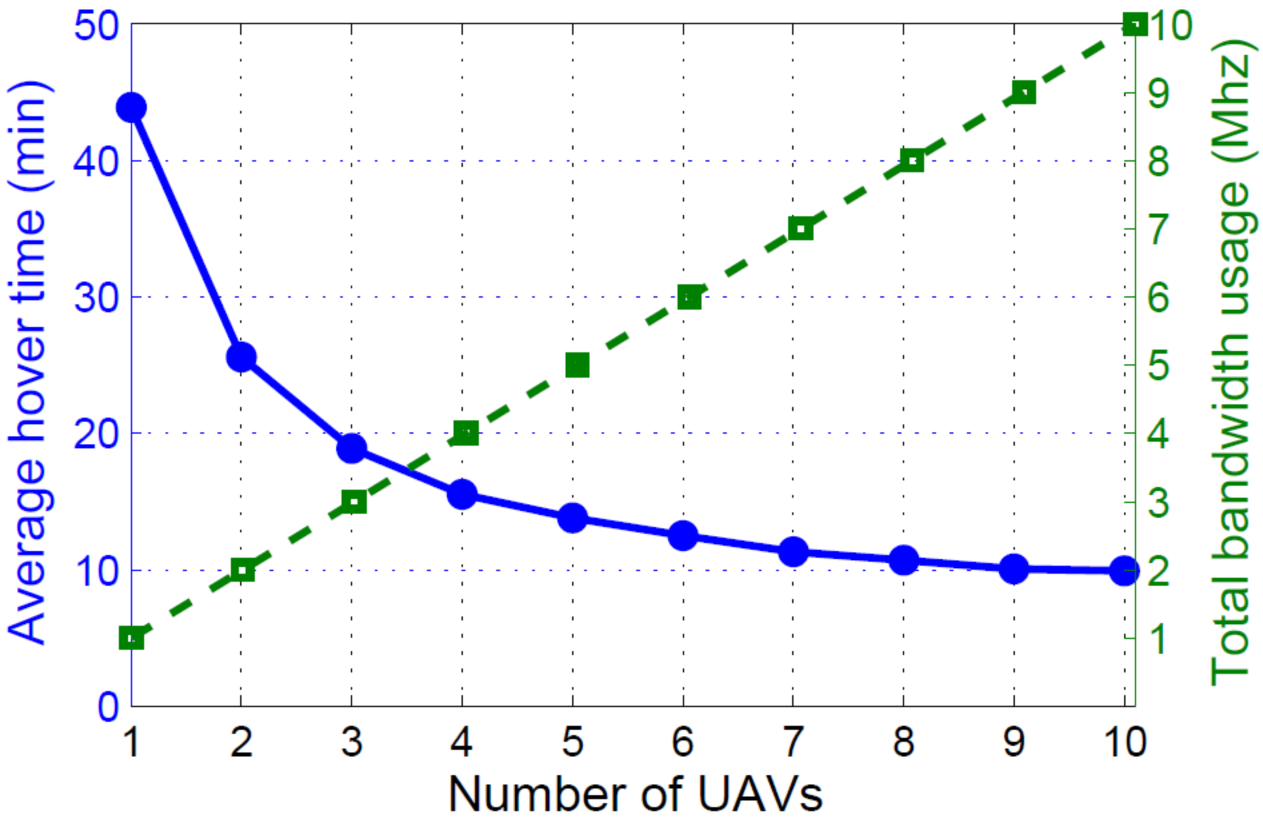
- Average hover time vs. control time

we consider $g_i(Na_i) = \alpha(Na_i)^2$, with α being an arbitrary constant factor.



Results: Scenario 2

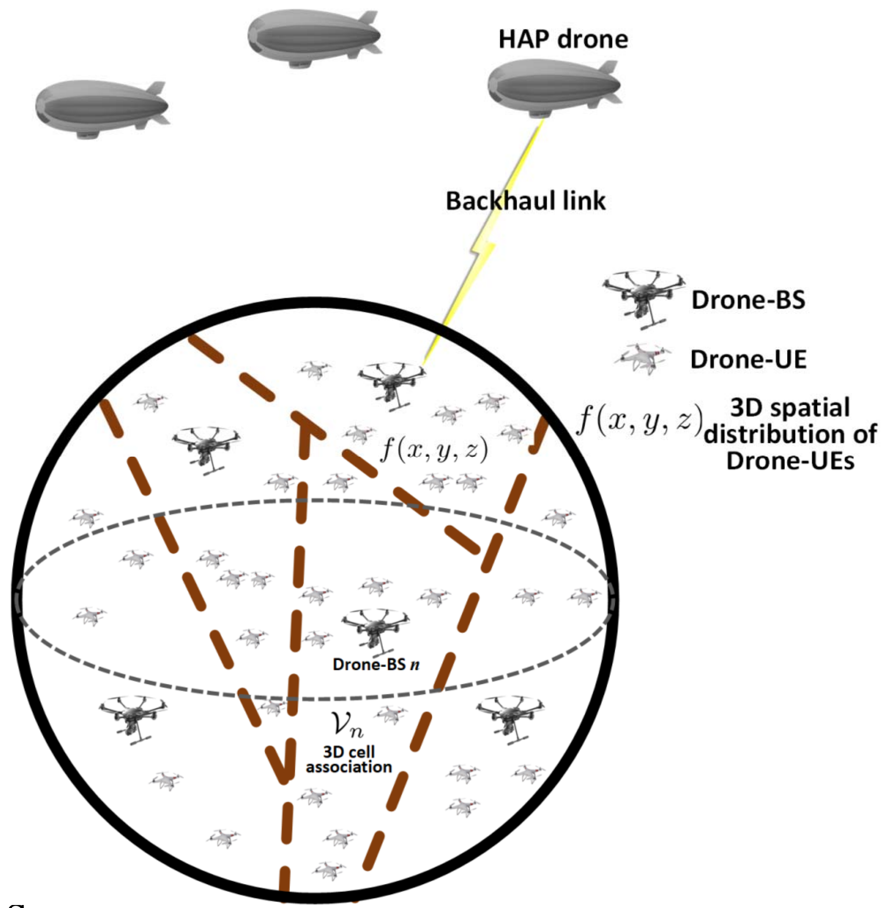
- Hover time and bandwidth tradeoff



Beyond 5G with UAVs: Foundations of a 3D Wireless Cellular Network

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

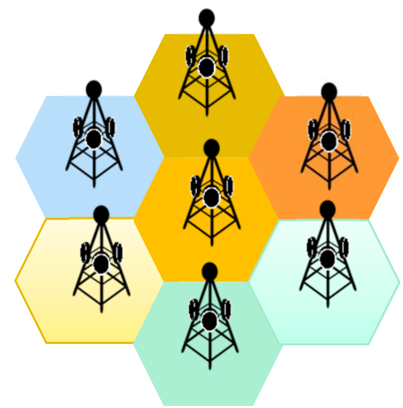
Optimal 3D cell association for minimum latency of drone-UEs using optimal transport theory

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

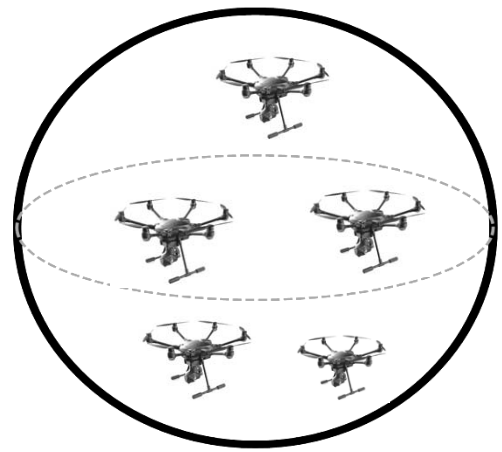
3D spatial distribution of drone-UEs

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?

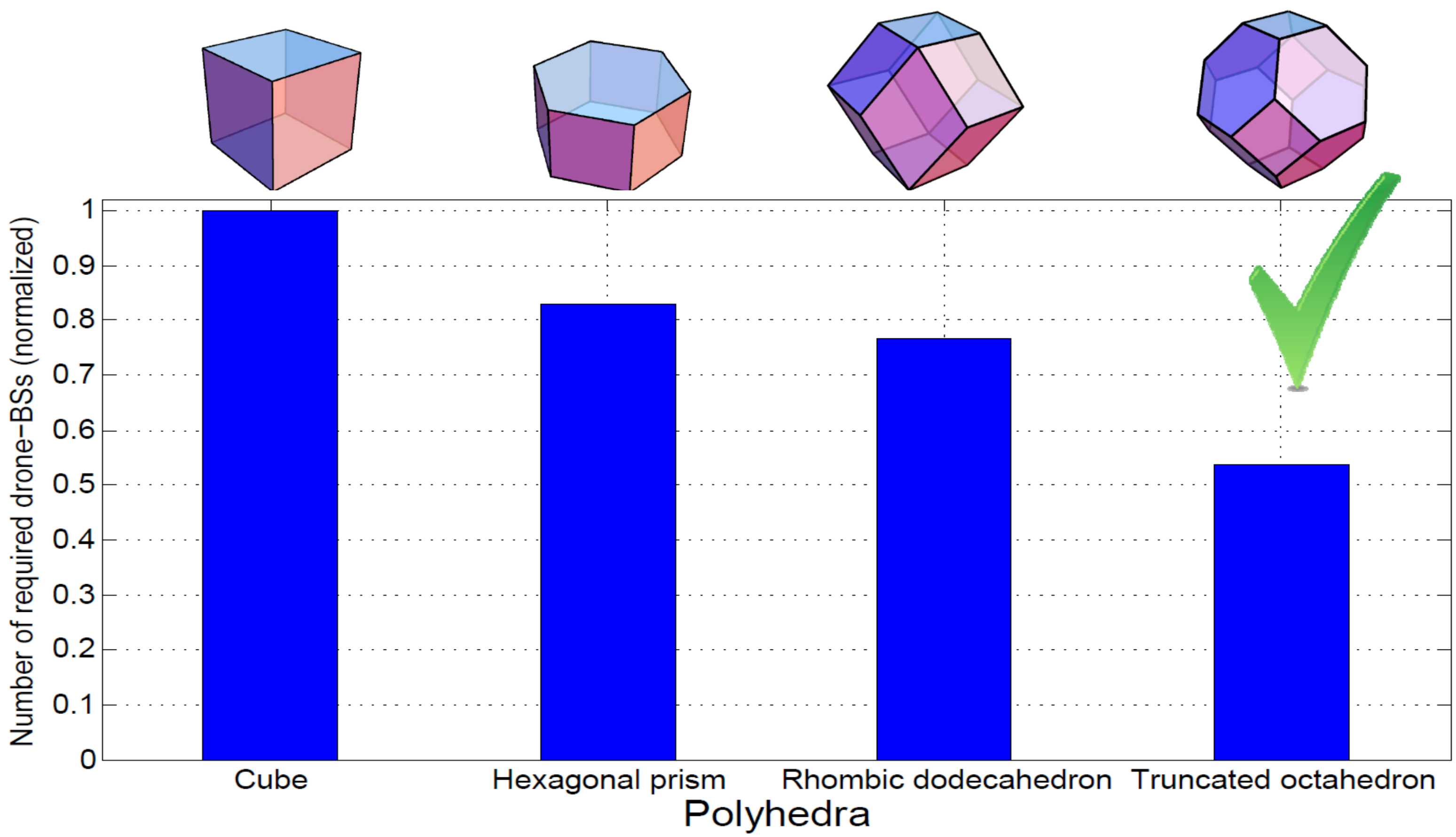


Criteria:

- 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

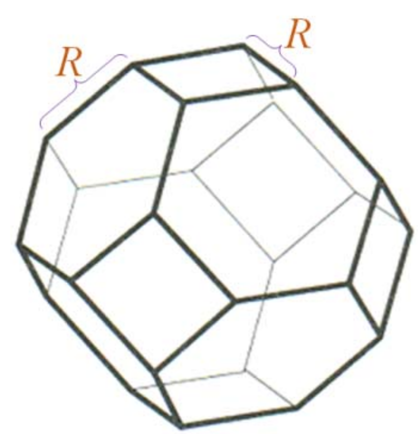
- Number of drone-BSs needed for full coverage of space
- Different **space filling polyhedra**



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

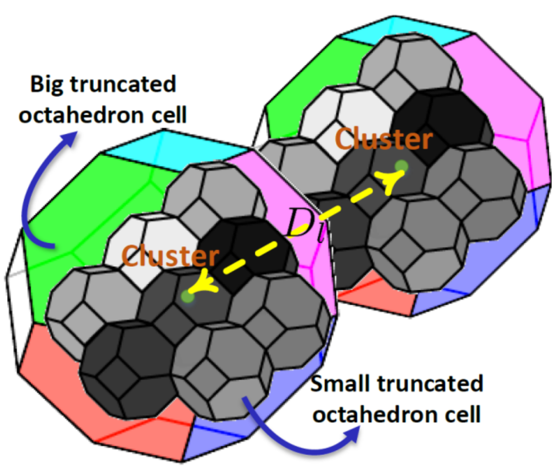
- **Theorem 1.** the three-dimensional locations of drone-BSs are:

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

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:

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

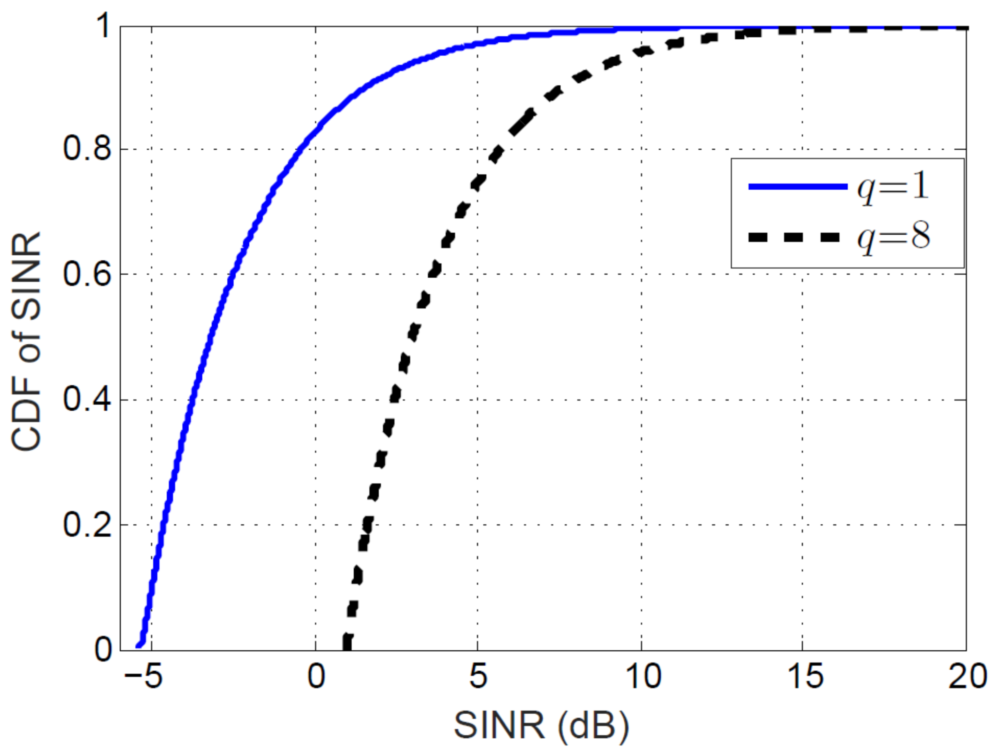


n_1, n_2, n_3, m_1, m_2, and m_3 are integers that satisfy above equations

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

Results: Frequency Planning

- Integer frequency reuse factors (q): 1 and 8



- Higher q : higher SINR but requires more bandwidth

Latency-Minimal 3D Cell Association

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

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

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

$f(x,y,z)$: Drone-UEs' distribution

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

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

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

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

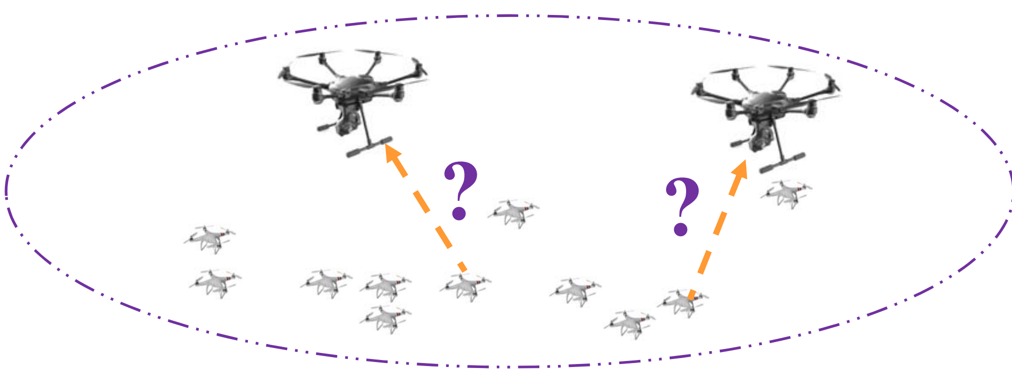
β : Packet length

B_n : Bandwidth

Challenging to solve

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



Steps:

- Existence of solution by the existence an optimal map
- Comparing optimal partitions and a non-optimal variation of those
- Characterizing the solution

Solution Characterization

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

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

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

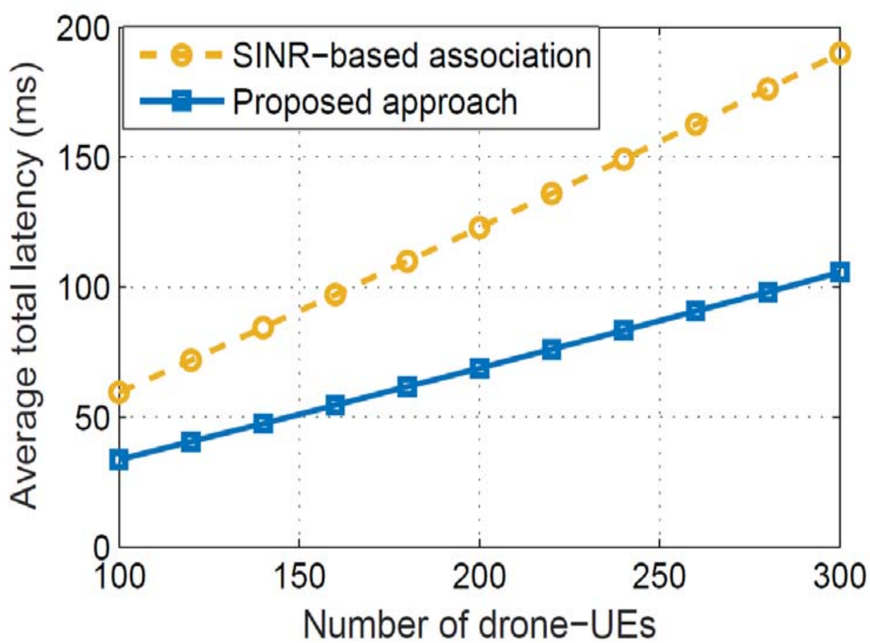
$$g_l{}'(K_l) = \left.\frac{dg_l(z)}{dz}\right|_{z=K_l}$$

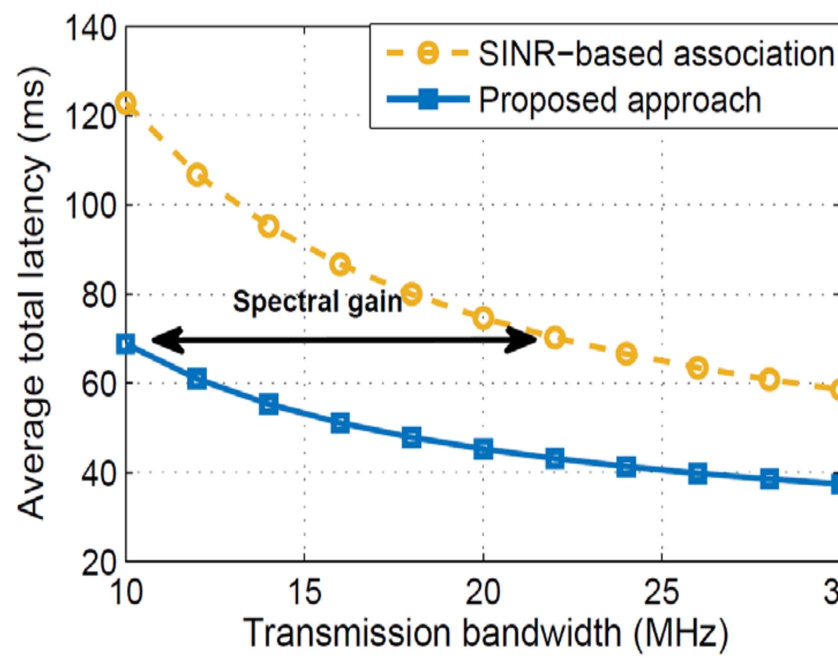
Note: 3D cell shapes depend on:

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

Results: 3D Cell Association

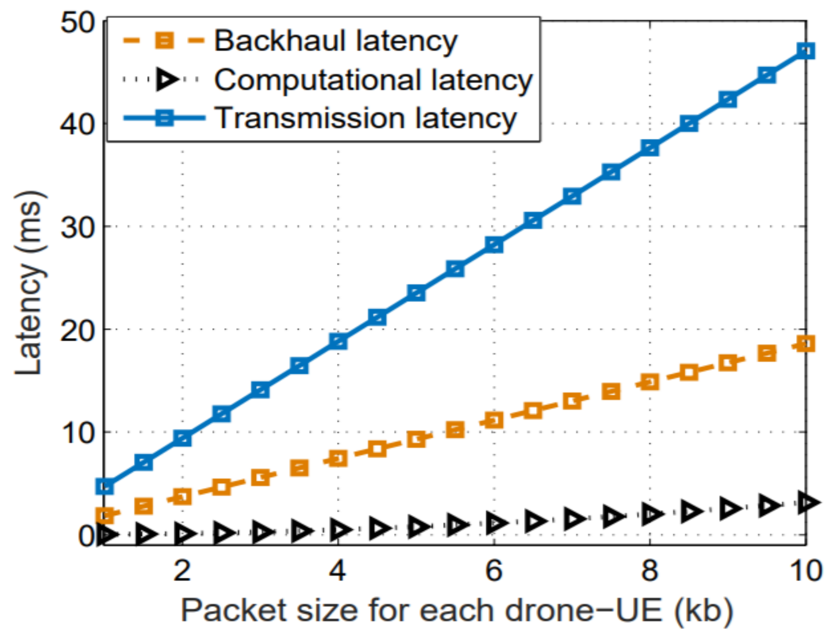
- Proposed approach vs. SINR-based association
  - Reduces latency
  - Improves spectral efficiency





Results: Latency

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

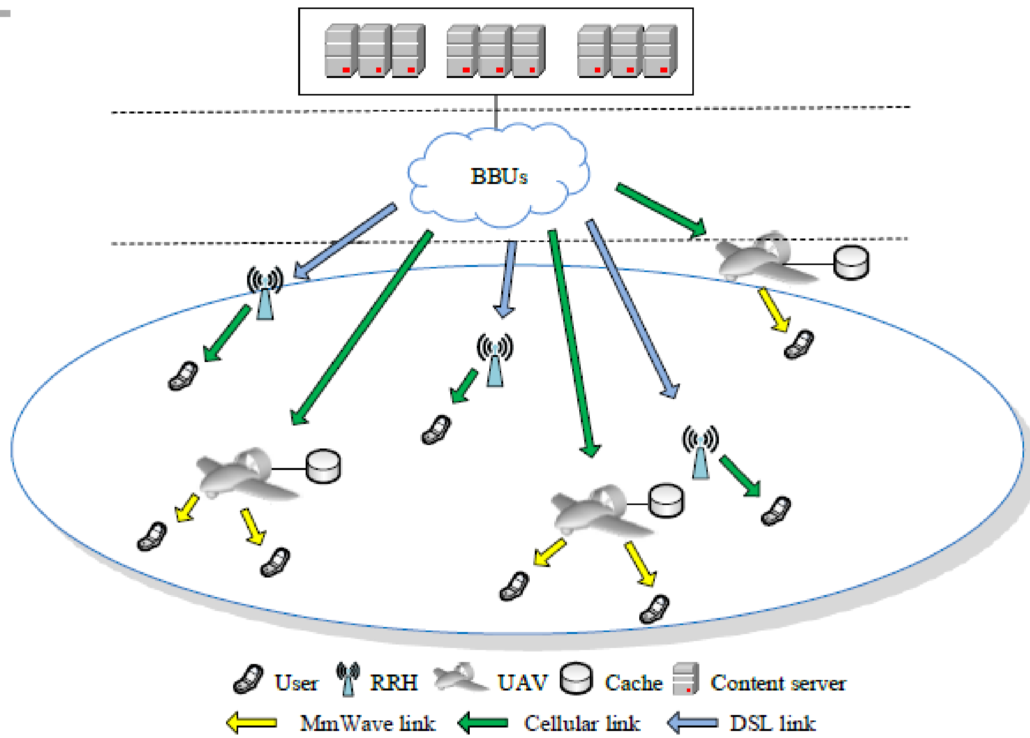


- M. Mozaffari, A. Taleb Zadeh Kasgari, Walid Saad, Mehdi Bennis, Merouane Debbah, "Beyond 5G with UAVs: Foundations of a 3D Wireless Cellular Network", https://arxiv.org/abs/1805.06532

Caching in the Sky: Proactive Deployment of Cache-Enabled Unmanned Aerial Vehicles for Optimized Quality-of-Experience

System Model

- Considerations:
  - Users mobility
  - Users' content request
  - Caching at UAVs
  - UAVs' deployment



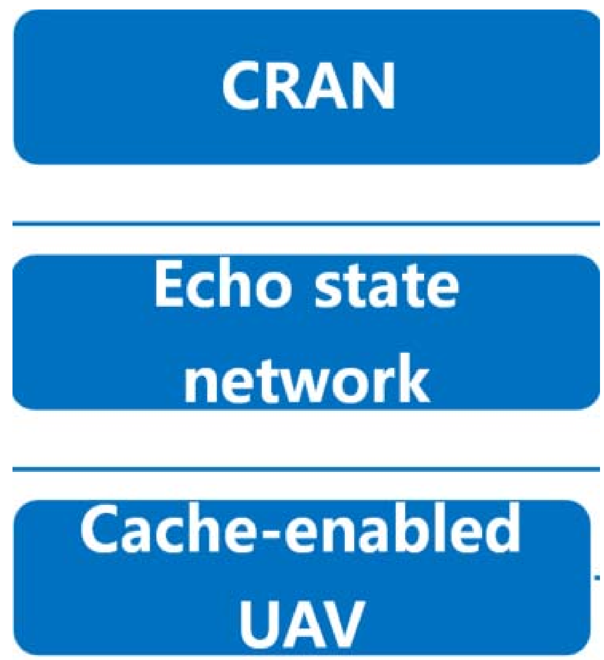
- Transmission links
  - (a) Content server->BBUs->RRHs->users
  - (b) Content server->BBUs->UAV>users
  - (c) Cache->UAVs->users

Main Objectives

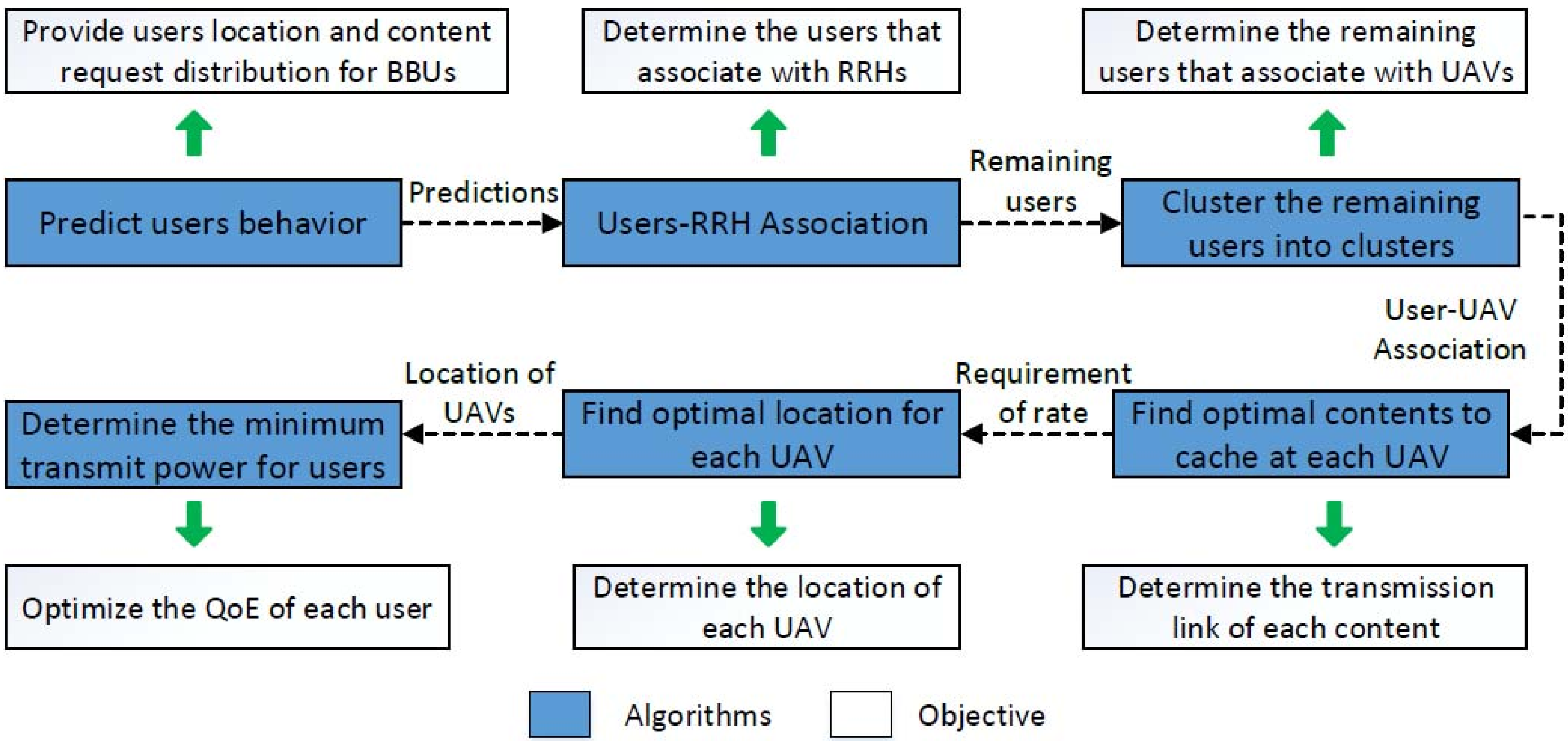
- Maximizing users' quality of experience (QoE) using minimum UAVs' transmit power

QoE	Poor	Fair	Good	Very Good	Excellent
Interval scale	0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	0.8-1

- Optimizing
  - Users association
  - UAVs' locations
  - Content caching



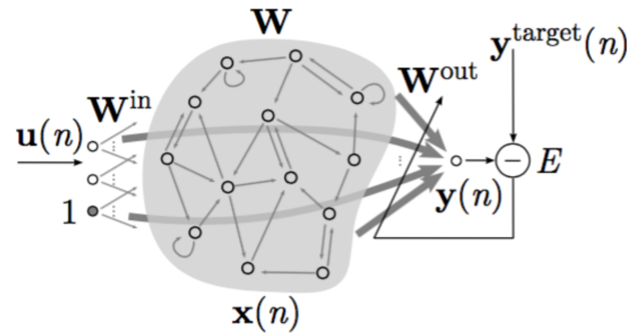
General Approach

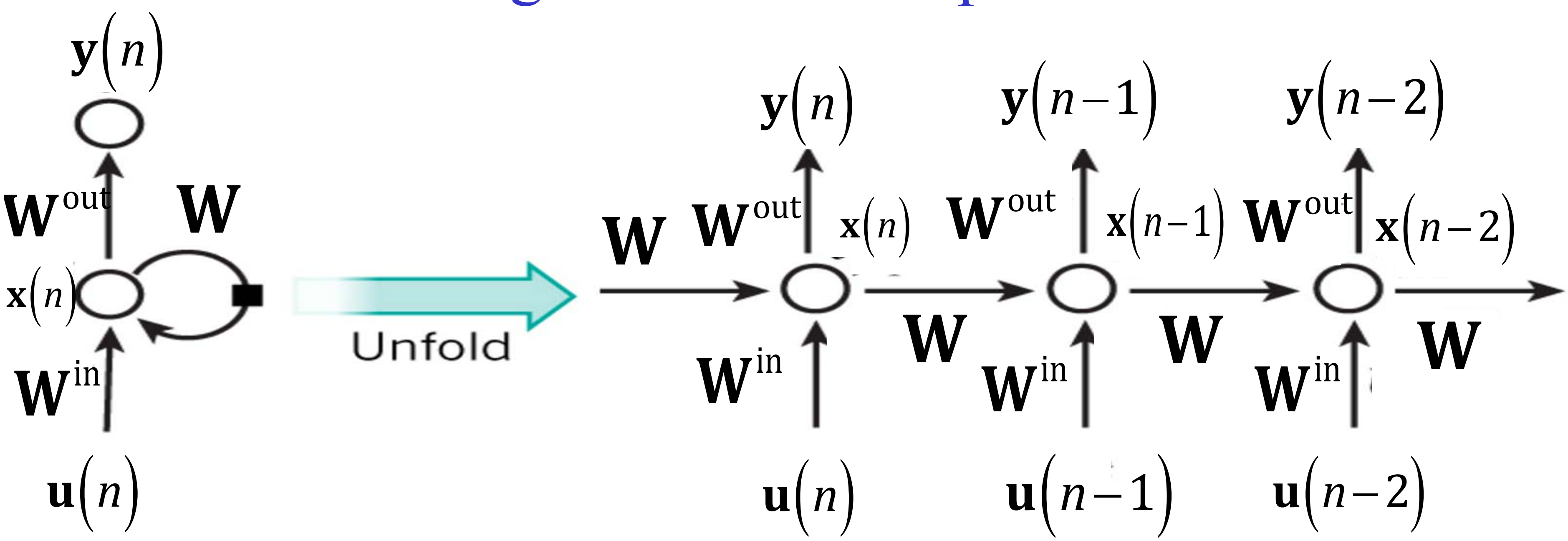


- For learning and predictions, we use the neural network framework of **echo state networks**

Echo State Networks

- Notion of "reservoir" (random)
- Only need to train the output layer via linear regression
- Good at dealing with time stamped data





Echo State Networks

Training Process

Step 1. generate a large random reservoir RNN $(\mathbf{W}^{\mathrm{in}}, \mathbf{W}, \alpha)$;

Step 2. run it using the training input $\mathbf{u}(n)$ and collect the corresponding reservoir activation states $\mathbf{x}(n)$;

$$\tilde{\mathbf{x}}(n) = \tanh\left(\mathbf{W}^{\mathrm{in}}[1; \mathbf{u}(n)] + \mathbf{W}\mathbf{x}(n-1)\right),$$
$$\mathbf{x}(n) = (1-\alpha)\mathbf{x}(n-1) + \alpha\tilde{\mathbf{x}}(n),$$

Step 3. compute the linear readout weights $\mathbf{W}^{\mathrm{out}}$ from the reservoir using linear regression, minimizing the MSE between $\mathbf{y}(n)$ and $\mathbf{y}^{\mathrm{target}}(n)$;

$$\mathbf{W}^{\mathrm{out}} = \mathbf{Y}^{\mathrm{target}}\mathbf{X}^{\mathrm{T}}\left(\mathbf{X}\mathbf{X}^{\mathrm{T}} + \beta\mathbf{I}\right)^{-1}$$

Usage Process

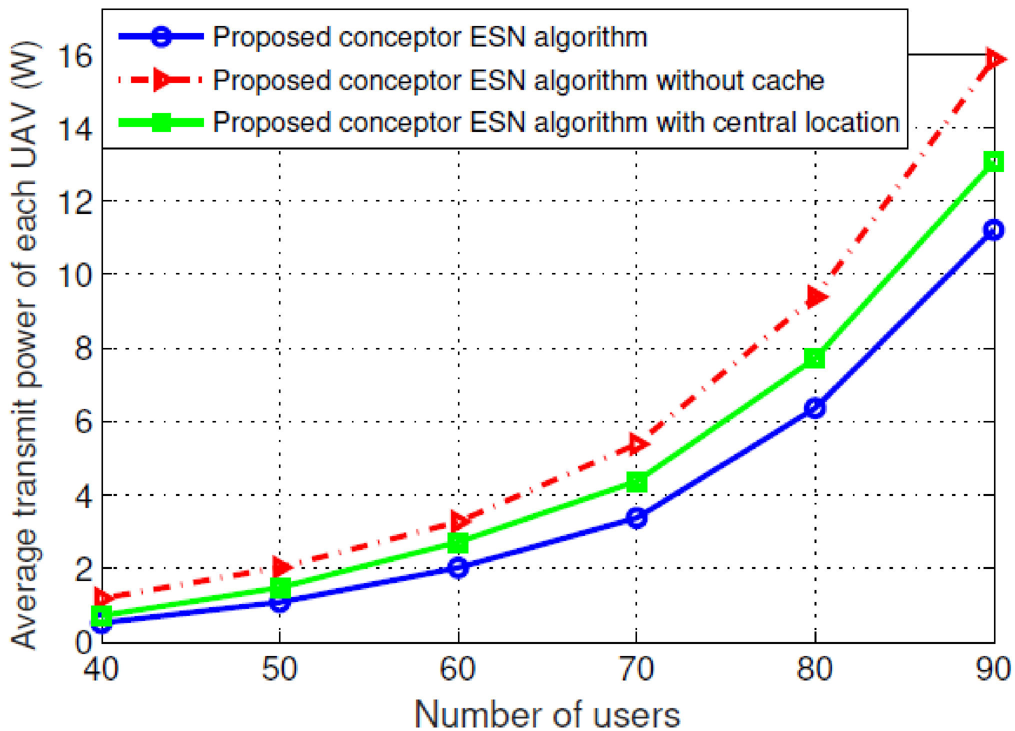
$$\tilde{\mathbf{x}}(n) = \tanh\left(\mathbf{W}^{\mathrm{in}}[1; \mathbf{u}(n)] + \mathbf{W}\mathbf{x}(n-1)\right),$$
$$\mathbf{x}(n) = (1-\alpha)\mathbf{x}(n-1) + \alpha\tilde{\mathbf{x}}(n),$$
$$\mathbf{y}(n) = \mathbf{W}^{\mathrm{out}}[1; \mathbf{u}(n); \mathbf{x}(n)],$$

ESN for Caching

- ESN model consists of
  - **Agents:** Baseband units of a CRAN
  - **Input:** the input is the users locations and context information (e.g., requested videos, etc.)
  - **Output:** the output is prediction of mobility patterns
  - **ESN model:** This is the reservoir model, without going through it now, it is composed of a set of matrices that enable the recurrent neural network learning/predictions
  - **Conceptor:** use of a week mobility as “pattern”
- For simulations, we use real data from BUPT and the Youku video website

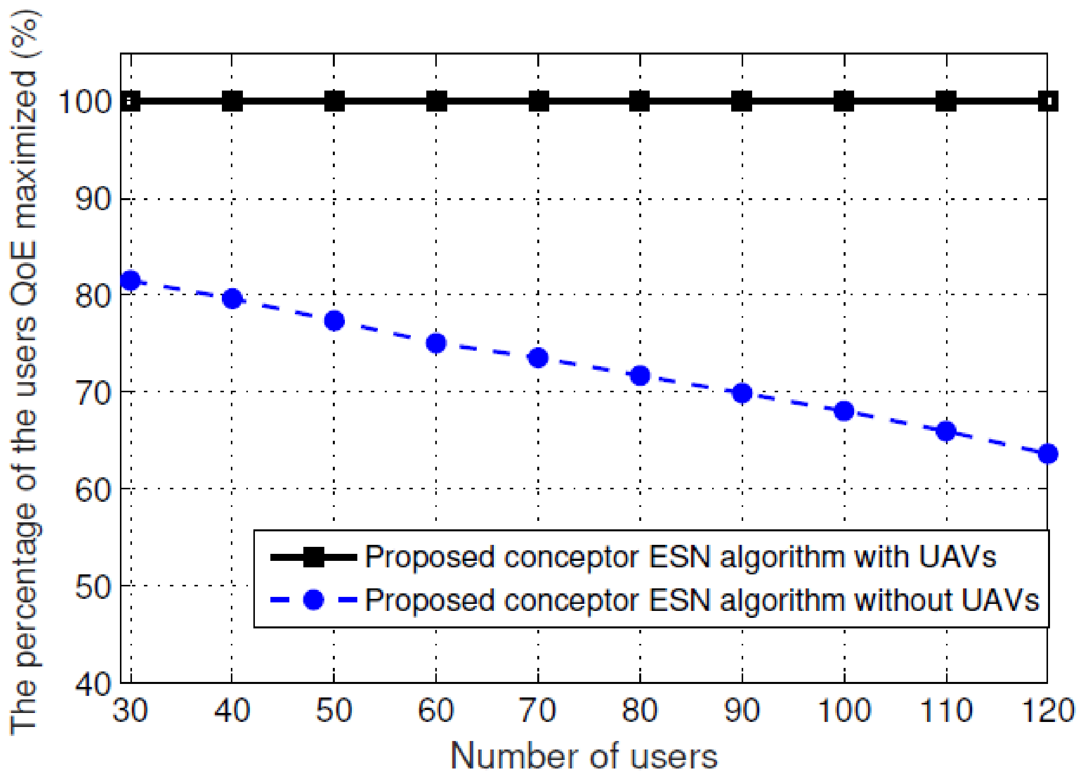
Results

- Average transmit power of each UAV vs. number of users
- Using proposed approach, 20% reduction in transmit power compared to other algorithms



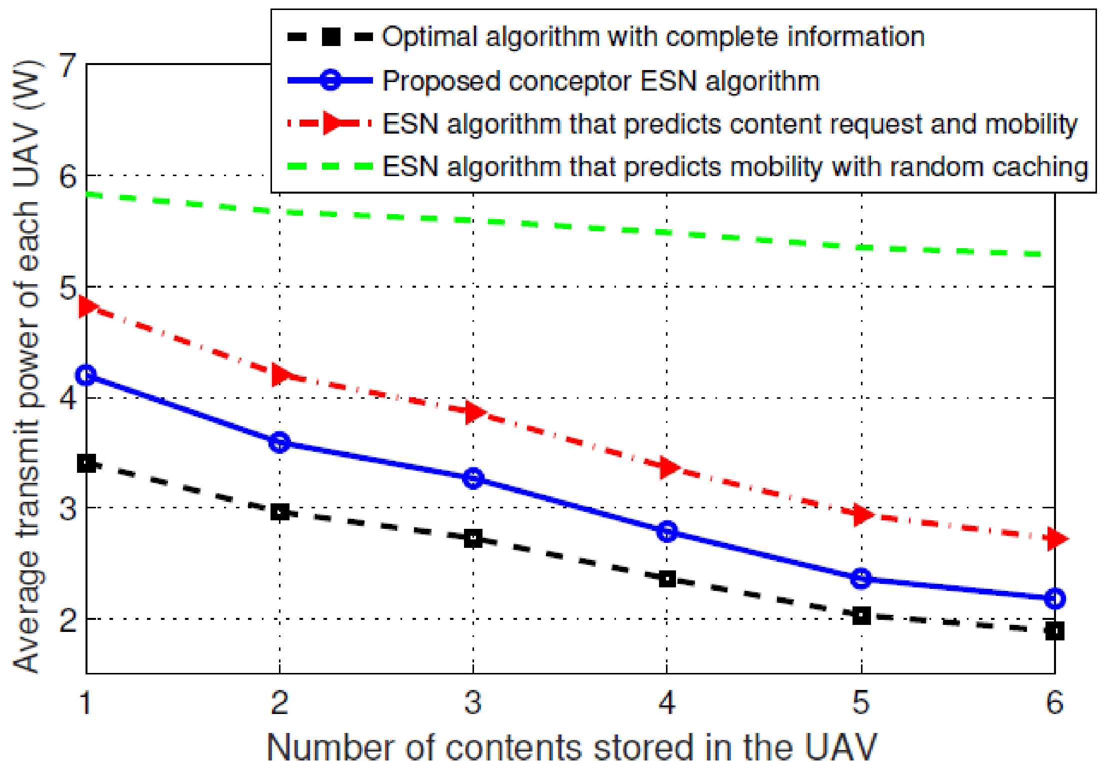
Results

- The percentage users with satisfied QoE versus the number of the users
- Using UAVs leads to a significant QoE improvement!



Results

- Decreasing transmit powers while increasing the number of storage units
  - UAV will directly transmit the requested contents to the users



Liquid State Machine Learning for Resource Allocation in LTE-U UAVs

System Model

- Consider the downlink of an LTE-U network composed of K dual-mode UAV-base stations and W ground WiFi access points
- The UAVs are equipped with cache storage units
  - UAVs can be deployed as flying base stations with caching capabilities
  - The UAV can cache a set $\mathcal{C}_k$ of C popular content that can be pre-fetched from a local cloud
  - Cloud-UAV fronthaul links are licensed, wireless links
- On the licensed band, we consider an FDD mode for the downlink of the LTE-U users, while we use a TDD mode with duty cycle for the unlicensed band
  - LTE-U transmissions will happen for a fraction of time ϑ over the unlicensed band, and will be muted for the rest of the slot
- The ground WiFi access points (WAPs) use a standard CSMA/CA

WiFi Data Rate Model

- The WiFi saturation capacity over the unlicensed band will be:

$$R(N_w) = \frac{P_{\text{tr}}(N_w) P_{\text{s}}(N_w) E[S]}{(1-P_{\text{tr}}(N_w))T_\sigma + P_{\text{tr}}(N_w)P_{\text{s}}(N_w)T_{\text{s}} + P_{\text{tr}}(N_w)(1-P_{\text{s}}(N_w))T_{\text{c}}}$$

users

Probability of occurrence of a transmission

Average packet size

Successful transmission probability

- T_c, T_s, and T_σ represent the average time the channel is sensed busy because of a successful transmission, during a collision, and the duration of an empty slot, respectively
  - Computed using conventional approaches
  - The WiFi network uses a standard DCF and RTS/CTS access schemes
- The per user WiFi rate will be: $R_w = \dfrac{R(N_w)(1-\vartheta)}{N_w}$

UAV Data Rate Model

- We use the air-to-ground channel model introduced by Hourani et al., in which the probability of a LoS connection depends on the ground environment, and, thus, the average path loss will be:

$$\bar{l}_{ki}^{l} = \Pr\left(l_{ki}^{\text{LoS}}\right) \times l_{ki}^{\text{LoS}} + \Pr\left(l_{ki}^{\text{NLoS}}\right) \times l_{ki}^{\text{NLoS}}$$

  - with

$$\Pr\left(l_{ki}^{\text{LoS}}\right) = \left(1 + X \exp\left(-Y\left[\phi_{ki} - X\right]\right)\right)^{-1}$$

  - and $l_{ki}^{\text{LoS}} = 20\log\left(\frac{4\pi d_{ki} f}{c}\right) + \eta_{\text{LoS}}^{l}, l_{ki}^{\text{NLoS}} = 20\log\left(\frac{4\pi d_{ki} f}{c}\right) + \eta_{\text{NLoS}}^{l}$

- The data rate on the licensed band will therefore be:

$$R_{lki}(u_{ki}(t)) = u_{ki}(t) F_l \log_2\left(1 + \frac{P_K 10^{\bar{l}_{ki}^{l}/10}}{\sum_{j \in \mathcal{K}, j \neq k} P_K 10^{\bar{l}_{ji}^{l}/10} + P_C h_i + \sigma^2}\right)$$

Fraction of licensed band for user *i*

Bandwidth

Fronthaul power

UAV Data Rate Model

- Over the unlicensed band, the data rate of the UAV will be:

$$R_{uki}(e_{ki}(t)) = e_{ki}(t)\vartheta F_u \log_2\left(1+\frac{P_K 10^{\bar{l}^u_{ki}/10}}{\sum_{j\in\mathcal{K}, j\neq k} P_K 10^{\bar{l}^u_{ji}/10}+\sigma^2}\right)$$

Fraction of time for unlicensed band

- The fronthaul UAV *k*-cloud rate for each associated user will be:

$$R_{Ck}(t) = \frac{F_C}{U_C(t)}\log_2\left(1+\frac{P_C \bar{L}_k}{\sum_{j\in\mathcal{K}, j\neq k} P_K 10^{\bar{l}_{ki}/10}+\sigma^2}\right)$$

Number of users at *t*

Average path loss

Queuing Model

- The queue length of user *i* at the start of slot *t* will be:

$$Q_i(t+1) = Q_i(t) - R_{ki}(t) + A_i(t)$$

Queue length

Data rate

Arrival rate

- The data rate will be

$$R_{ki}\left(u_{ki}(t), e_{ki}(t)\right) = \begin{cases} R_{lki}\left(u_{ki}(t)\right), & \text{link (a),} \\ R_{uki}\left(e_{ki}(t)\right), & \text{link (b),} \\ \frac{R_{uki}(e_{ki}(t))R_{Ck}(t)}{R_{uki}(e_{ki}(t))+R_{Ck}(t)}, & \text{link (c),} \\ \frac{R_{lki}(u_{ki}(t))R_{Ck}(t)}{R_{lki}(u_{ki}(t))+R_{Ck}(t)}, & \text{link (d).} \end{cases}$$

  - Link (a) is the UAV-user link over the licensed band
  - Link (b) is the UAV-user link over the unlicensed band
  - Link (c) is the cloud-UAV-user licensed band link
  - Link (d) is the cloud-UAV-user unlicensed band link

Problem Formulation

- Queue stability will be used to measure the delay:

$$\lim_{t \to \infty} \frac{Q_i(t)}{t} = 0 \qquad R_{ki}(t) \geq A_i(t)$$

- The key goal is to solve the following resource management problem:

$$\max_{\boldsymbol{u}, \boldsymbol{e}, \mathcal{C}_k, \mathcal{U}_k} \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{U}_k} \mathbb{1}_{\left\{\lim\limits_{t \to \infty} \frac{Q_i(t)}{t} = 0\right\}} = \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{U}_k} \mathbb{1}_{\{R_{ki}(u_{ki}(t), e_{ki}(t)) \geq A_i(t)\}}$$

$$\begin{aligned} \text{s. t.} \quad & R_w \geq \gamma, \\ & \sum_{i \in \mathcal{U}} u_{ki}(t) \leq 1, \quad \forall k \in \mathcal{K}, \\ & \sum_{i \in \mathcal{U}} e_{ki}(t) \leq 1, \quad \forall k \in \mathcal{K}, \end{aligned}$$

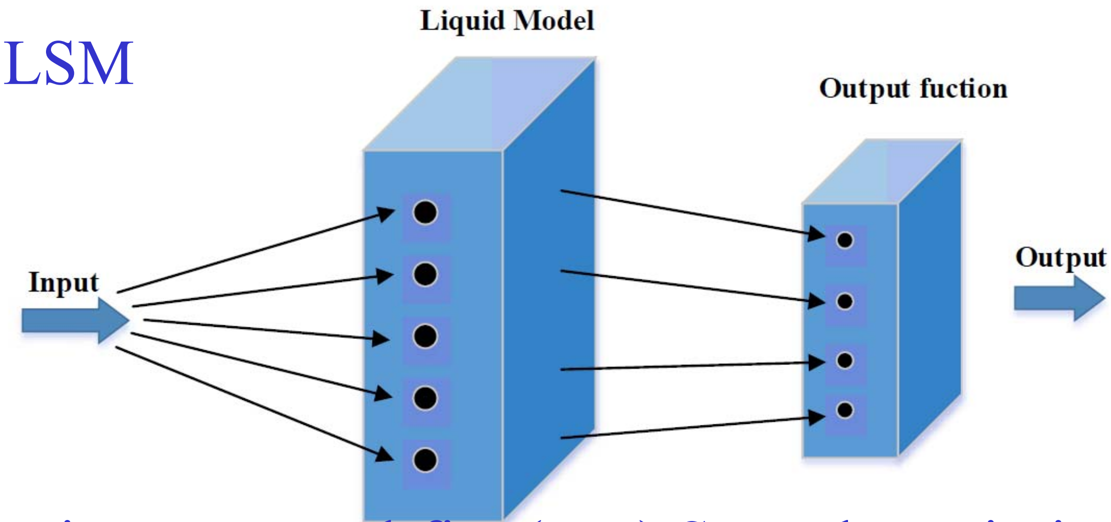
  - Challenging problem because it includes both content predictions/caching and spectrum management which is non-convex and complex
  - **Solution? Neural networks for predictions AND resource management!**

Liquid State Machines

- We need an algorithm that can: a) track the network over time, b) store user information, and c) rapidly find the resource management solution
  - We use spiking neural networks (SNNs) since they can capture accurate activation of neurons which enhance their predictive capabilities
  - SNNs have two major advantages: fast real-time decoding of input signals that are continuous and a temporal dimension that can help a high volume of information for predictions
- However, general SNNs are computational complex to train
  - Solution via **liquid state machines (LSMs)**
  - LSMs are SNNs that are easy to train as they use the concept of reservoir computing (basically random training) to make them amenable to easy implementation

LSM for Predictions

- Basic architecture of LSM



- The "liquid" is a leaky-integrate-and-fire (LIF) SNN that mimics exactly a biological neuron
- The input in our model is $\boldsymbol{x}_j(t) = [x_{j1}(t), \cdots, x_{jN_x}(t)]^{\mathrm{T}}$ which is a vector that represents the users' context information
- The output is a request distribution vector $\boldsymbol{y}_j(t) = [p_{tj1}, p_{tj2}, \ldots, p_{tjN}]$
- The output function builds the relation between LSM state and the content request distribution

LSM for Predictions

- The output function is trained in an offline manner using ridge regression:

$$\boldsymbol{f}_j = \boldsymbol{y}_{T,j}\boldsymbol{v}_j^{\mathrm{T}}\left(\boldsymbol{v}_j^{\mathrm{T}}\boldsymbol{v}_j + \delta^2 \boldsymbol{I}\right)^{-1}$$

Target output

LSM state sequence

Learning rate

Identity matrix

- Then, the prediction of the output can be found:

$$\boldsymbol{y}_j(t) = \boldsymbol{f}_j \boldsymbol{v}_j(t)$$

- We now need to define another LSM for solving the resource management optimization problem

LSM for Resource Management

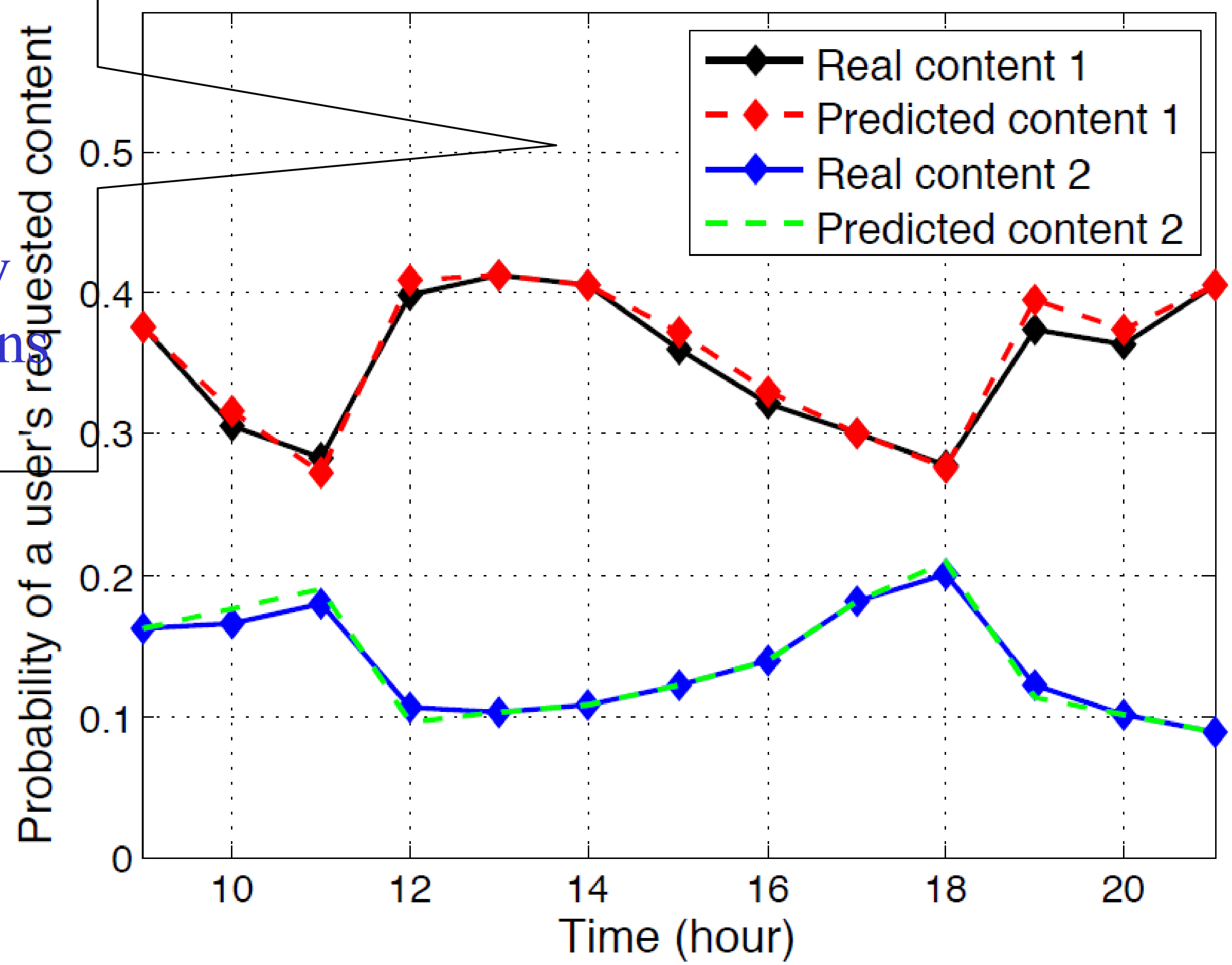
- The UAVs are the agents that run the LSM for resource management
- The input is a vector $\boldsymbol{m}_k(t)$ of actions observed by UAV k on other UAVs, with each action being a user association scheme
- Using this input and one of our previous results, we can recast on cached content, we can recast the original optimization as a convex problem to choose the actions
- The output of the LSM is a vector $\boldsymbol{b}_k(t)$ that provides the resource allocation results, with each element being the expected number of stable queue users:

$$b_{ki}(t) = \sum_{\boldsymbol{a}_{-k} \in \mathcal{A}_{-k}} b_{ki,\boldsymbol{a}_{-k}}(a_{ki}, \boldsymbol{a}_{-k}) \pi_{-k,\boldsymbol{a}_{-k}}$$

- This is used with the output function to solve our original problem

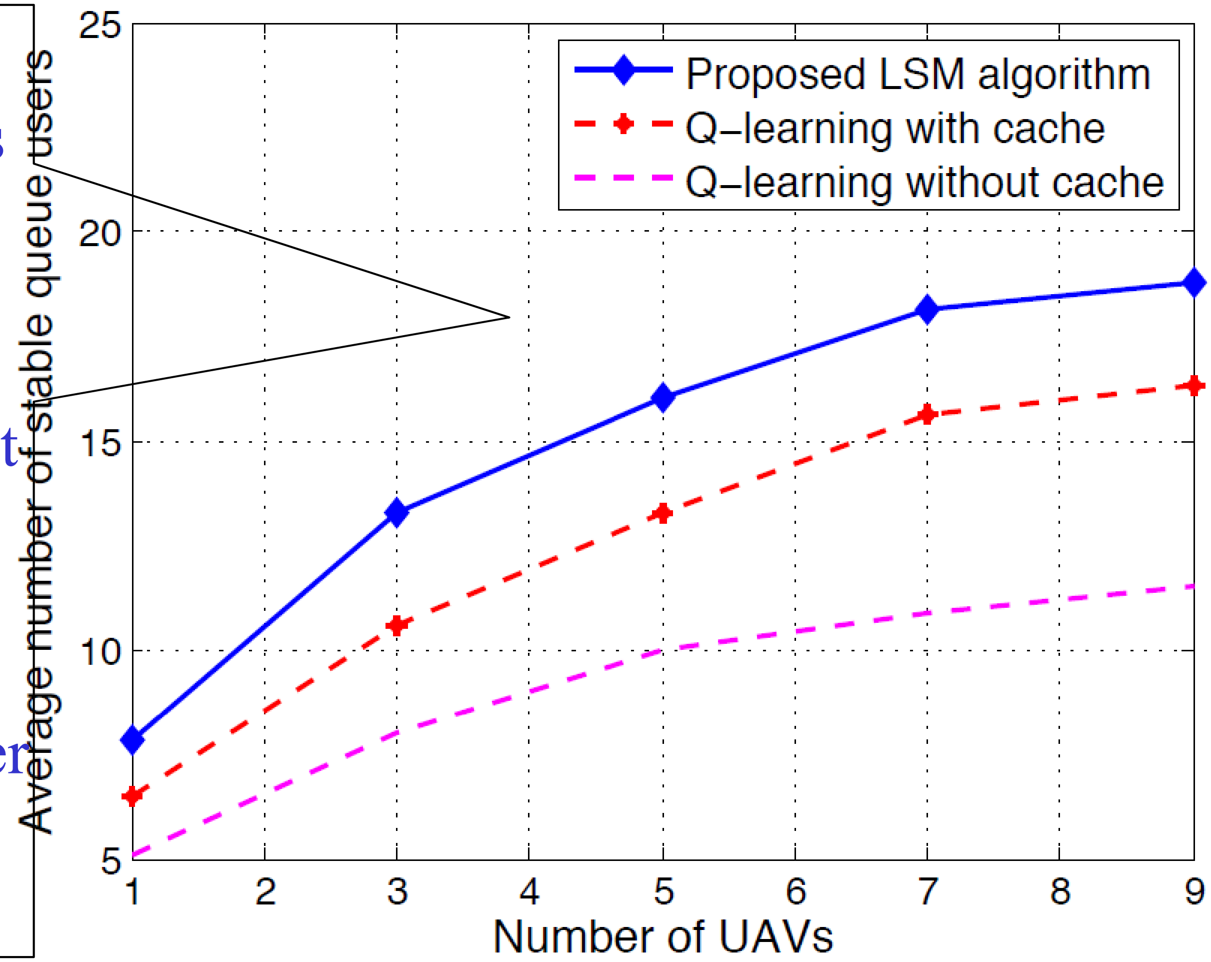
Simulation Results

- Real data from Youku
- LSM provide very accurate predictions



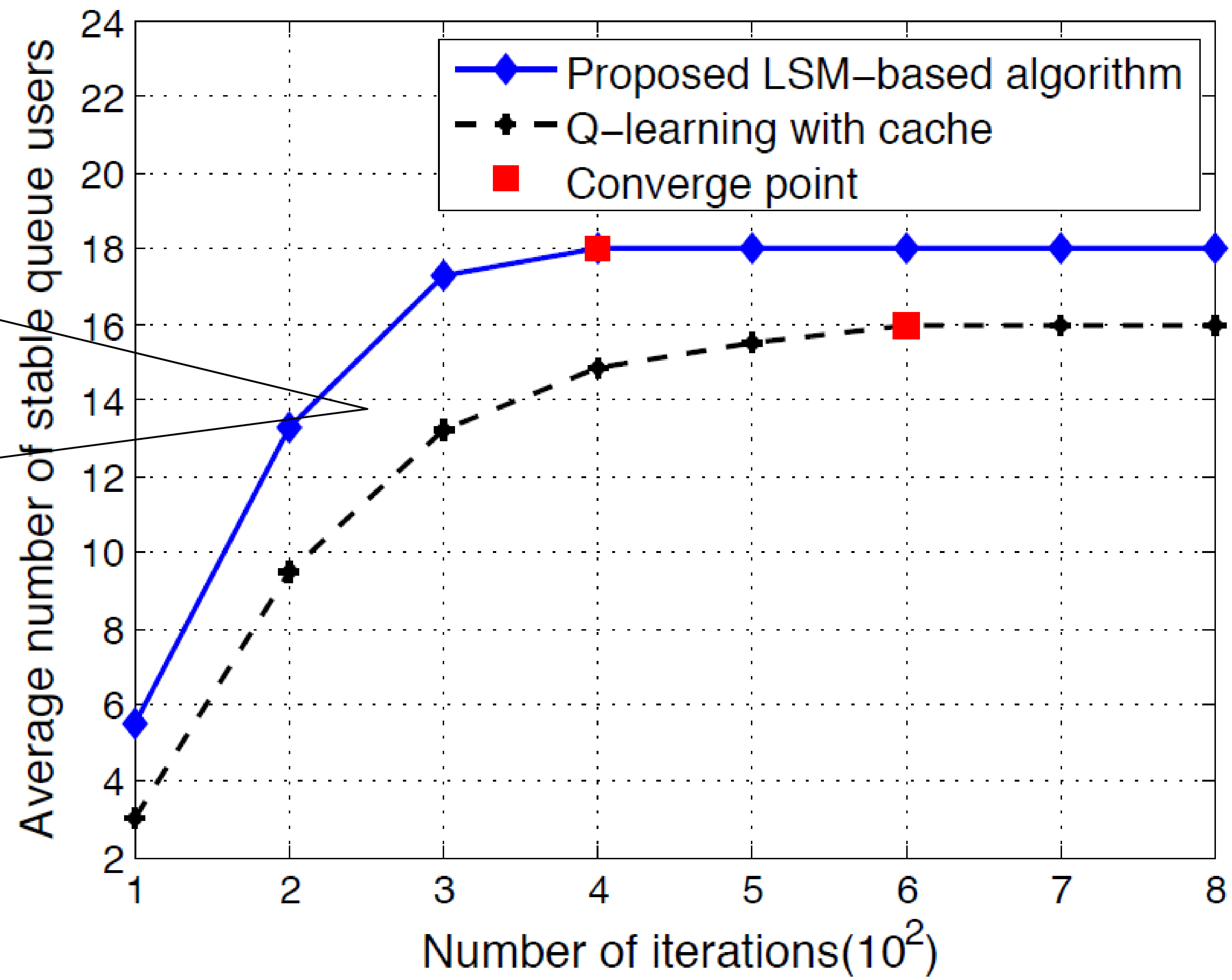
Simulation Results

- The average number of stable queue users increases with network size
- Caching brings about substantial gains, even without LSM
- LSM provides further gains



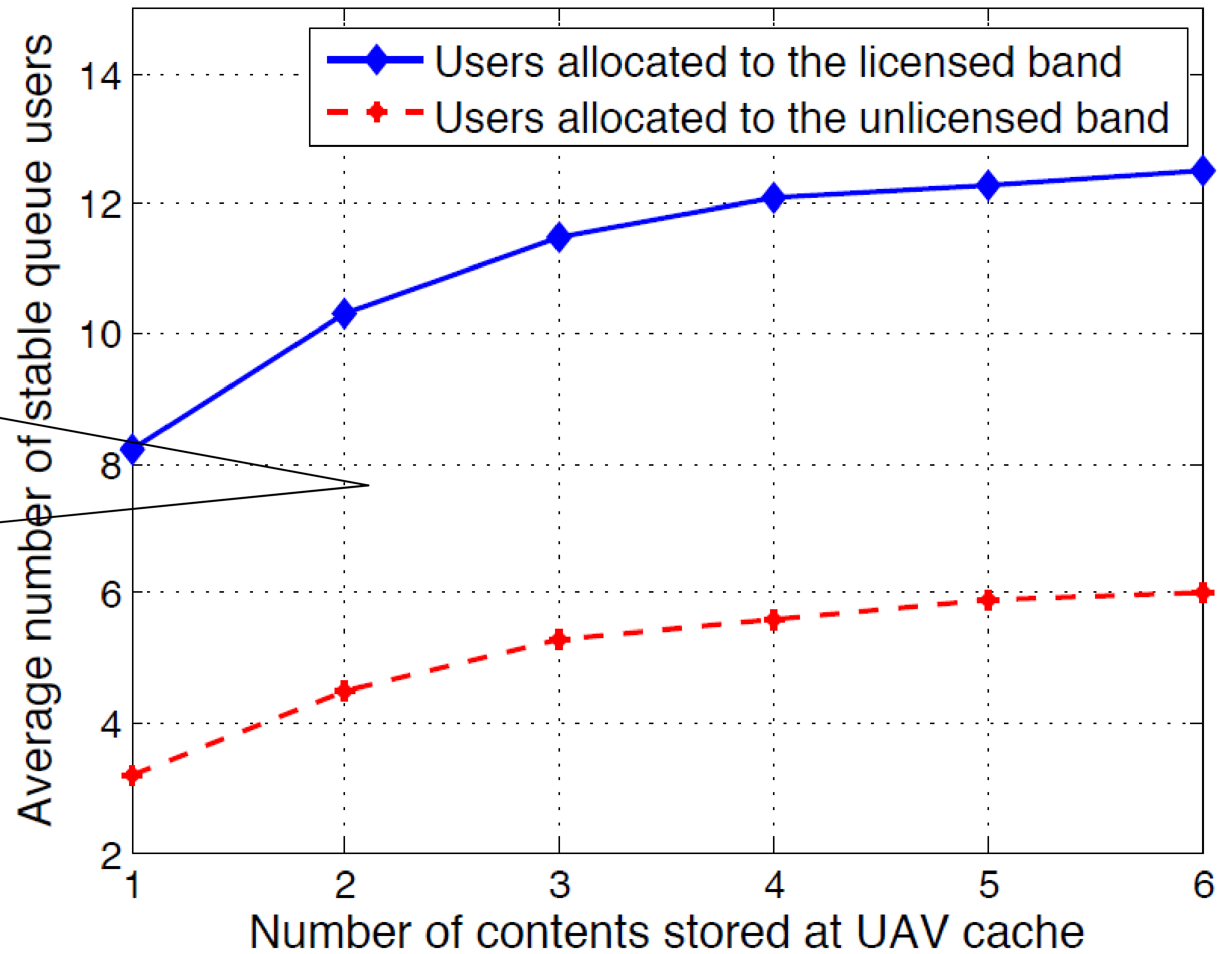
Simulation Results

The proposed LSM algorithm leverage the power of SNNs to substantially reduce convergence time (about 1/3 less than Q-learning)



Simulation Results

The more we can cache, the more users we can serve with stable queues



Cellular-Connected UAVs over 5G: Deep Reinforcement Learning for Interference Management

System Model

- Uplink of a cellular network composed of S base stations (BSs), Q ground users, and J cellular-connected UAVs
  - UAVs must co-exist with ground users and share resource blocks
- UAVs are assumed to be flying at a constant altitude (different for different UAVs) and collecting data (e.g., surveillance, sensing, etc.) that needs to be transmitted to the ground BSs
  - Each UAV has a specific mission and needs to move from an origin to a destination while transmitting data along the way
- For ease of exposition, we consider a virtual grid that the UAVs use for their mobility, i.e., they move along the centers of small grids
  - Areas within the grid are chosen to be sufficiently small

UAV-BS Transmission Model

- The SINR for UAV *j*'s transmission to a ground BS *s*, over RB *c* is:

$$\Gamma_{j,s,c,a} = \frac{P_{j,s,c,a} h_{j,s,c,a}}{I_{j,s,c} + B_c N_0}$$

UAV power

Rician channel

Total Interference (ground and air)

Bandwidth

- The achievable rate for a UAV *j* will then be given by:

RBs

$$R_{j,s,a} = \sum_{c=1}^{C_{j,s}} B_c \log_2(1 + \Gamma_{j,s,c,a})$$

- We also consider queuing latency, using an M/D/1 model:

Packet arrivals

$$\tau_{j,s,a} = \frac{\lambda_{j,s}}{2\mu_{j,s,a}(\mu_{j,s,a} - \lambda_{j,s})} + \frac{1}{\mu_{j,s,a}}$$

Data rate

Ground Users Data Rate Model

- For the ground users, the achievable data rate will be given by:

$$R_{q,s} = \sum_{c=1}^{C_{q,s}} B_c \log_2 \left(1 + \frac{P_{q,s,c} h_{q,s,c}}{I_{q,s,c} + B_c N_0}\right)$$

Total Interference (ground and air)

- Ground users can potentially be significantly affected by interference stemming from flying UAVs (due to the drones' better channel towards the ground BSs)
- Our objectives will therefore be to answer the following key questions:
  - How can we design a wireless-aware path planning mechanism for cellular-connected UAVs?
  - How can the designed path plan optimize the UAVs' mission goals, while minimizing impact on the ground network?

Problem Formulation

- We can pose our path planning problem as follows:

$$\min_{\widehat{\boldsymbol{P}},\boldsymbol{\alpha},\boldsymbol{\beta}} \varrho \sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{c=1}^{C_{j,s}}\sum_{a=1}^{A}\sum_{r=1,r\neq s}^{S} \frac{\widehat{P}_{j,s,a} h_{j,r,c,a}}{C_{j,s}}$$

$$+\varpi \sum_{j=1}^{J}\sum_{a=1}^{A}\sum_{b=1,b\neq a}^{A} \alpha_{j,a,b} + \phi \sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{a=1}^{A} \beta_{j,s,a}\tau_{j,s,a},$$

$$\sum_{b=1,b\neq a}^{A} \alpha_{j,b,a} \leq 1 \;\; \forall j \in \mathcal{J}, a \in \mathcal{A},$$

$$\sum_{a=1,a\neq o_j}^{A} \alpha_{j,o_j,a}{=}1 \;\; \forall j \in \mathcal{J}, \quad \sum_{a=1,a\neq d_j}^{A} \alpha_{j,a,d_j}{=}1 \;\; \forall j \in \mathcal{J},$$

$$\sum_{a=1,a\neq b}^{A} \alpha_{j,a,b} - \sum_{f=1,f\neq b}^{A} \alpha_{j,b,f}{=}0 \; \forall j \in \mathcal{J}, b \in \mathcal{A}\; (b \neq o_j, b \neq d_j),$$

$$\sum_{c=1}^{C_{j,s}} \Gamma_{j,s,c,a} \geq \beta_{j,s,a}\overline{\Gamma}_j \quad \forall j \in \mathcal{J}, s \in \mathcal{S}, a \in \mathcal{A}, .,$$

$$0 \leq \widehat{P}_{j,s,a} \leq \overline{P}_j \;\; \forall j \in \mathcal{J}, s \in \mathcal{S}, a \in \mathcal{A},$$

$$\sum_{s=1}^{S} \beta_{j,s,a} - \sum_{b=1,b\neq a}^{A} \alpha_{j,b,a} = 0 \;\; \forall j \in \mathcal{J}, a \in \mathcal{A},$$

Tradeoff between interference to ground, delay, and path length

Each area is visited once

Maintain origin-destination

Arrive/leave same area

SINR/power constraints

One BS per UAV

Game-Theoretic Approach

- Problem is challenging to solve in a centralized manner, especially to do joint power allocation, navigation, and cell association
- Objective functions are coupled through interference => **a game-theoretic approach is appropriate!**
- We formulate a dynamic game:

State space: distance/orientation

$$\mathcal{G} = (\mathcal{J}, \mathcal{T}, \mathcal{Z}_j, \mathcal{V}_j, \Pi_j, u_j)$$

UAVs

Stages

Actions

Distributions

Utility functions

- The utility functions can be defined as follows:

$$u_j(\boldsymbol{v}_j(t), \boldsymbol{z}_j(t), \boldsymbol{z}_{-j}(t)) = \begin{cases} \Phi(\boldsymbol{v}_j(t), \boldsymbol{z}_j(t), \boldsymbol{z}_{-j}(t)) + C, \text{ if } \delta_{j,d_j,a}(t) < \delta_{j,d_j,a'}(t-1), \\ \Phi(\boldsymbol{v}_j(t), \boldsymbol{z}_j(t), \boldsymbol{z}_{-j}(t)), \text{ if } \delta_{j,d_j,a}(t) = \delta_{j,d_j,a'}(t-1), \\ \Phi(\boldsymbol{v}_j(t), \boldsymbol{z}_j(t), \boldsymbol{z}_{-j}(t)) - C, \text{ if } \delta_{j,d_j,a}(t) > \delta_{j,d_j,a'}(t-1), \end{cases}$$

Lagrangian conversion of centralized case

Solution Approach

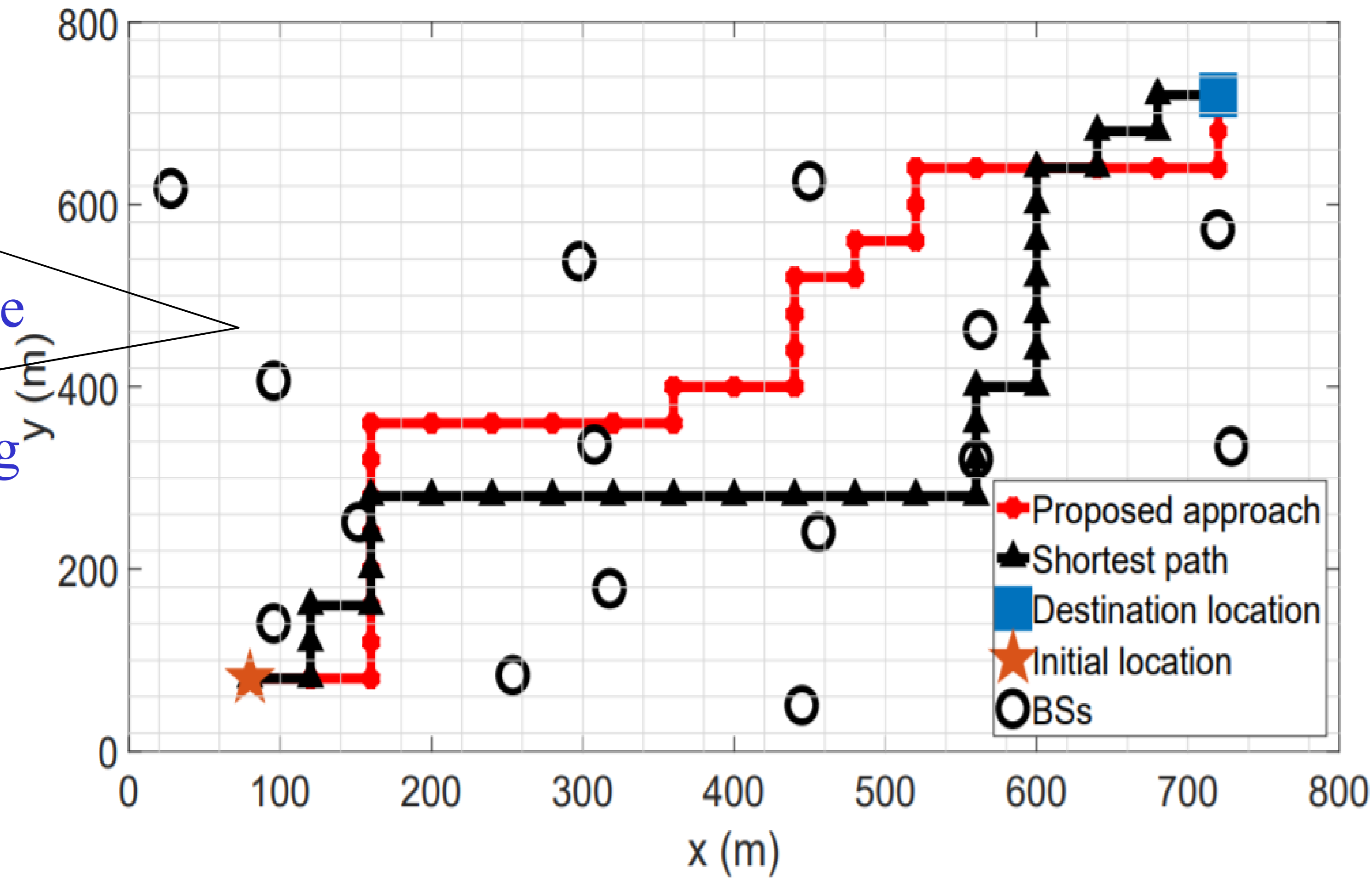
- Since the game is dynamic and has a large action space, it is challenging to analytical characterize the subgame perfect Nash equilibrium (SPNE)
  - Such characterization may also require full knowledge of the system and state, which is not very practical
- We will seek to develop a reinforcement learning (RL) algorithm that enables the UAVs to autonomously find the SPNE
  - RL algorithm with predictive capabilities is needed to operate with minimal information
  - Actions are time varying => need dynamic RL predictions and highly adaptive algorithm
  - **Recurrent neural networks!**

ESN for UAV

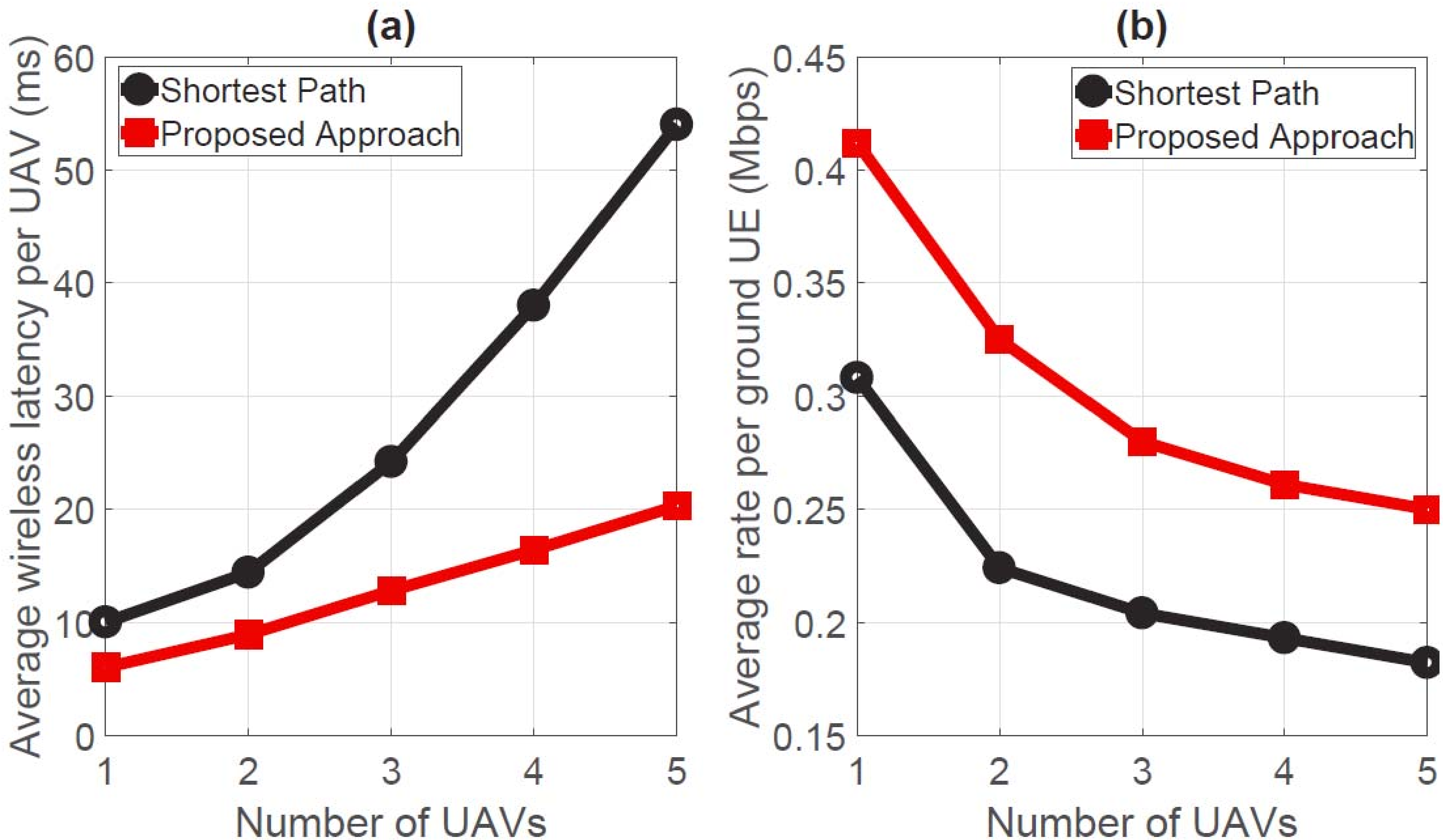
- We not only need to deal with time-stamped data, but also with large action sets
  - We will propose a novel **deep** ESN architecture
  - **Input:** the input to the first layer is the external network state while input to subsequent layers are previous layers
  - **Output:** the output is estimation of utility function
  - **ESN model:** This is the reservoir model, without going through it now, it is composed of a set of matrices that enable the RNN learning/predictions and is trained by our network state
- When it converges, the algorithm will find an SPNE, but establishing general convergence is challenging

Simulation Results

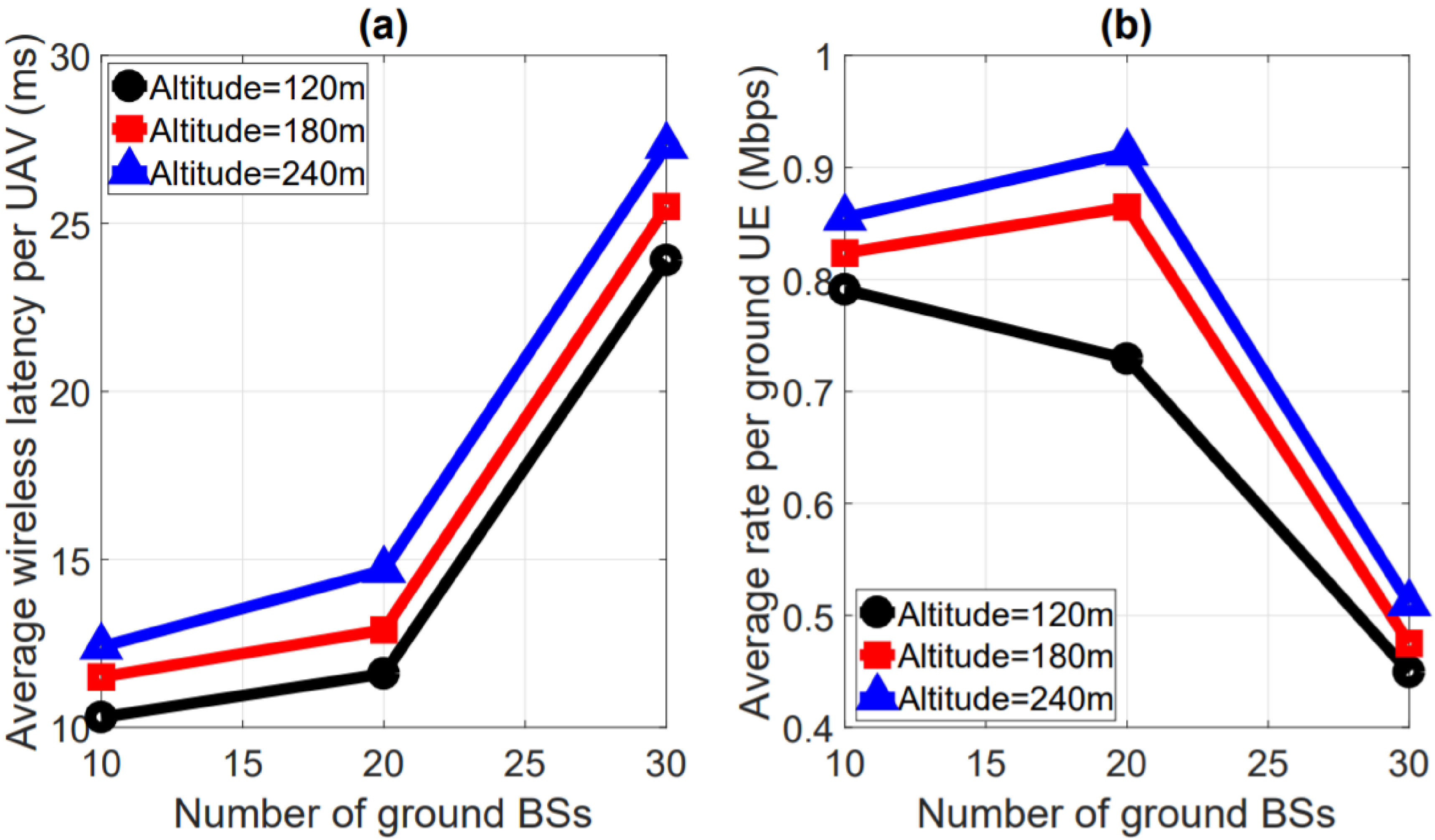
Proposed wireless-aware approach avoids causing ground interference



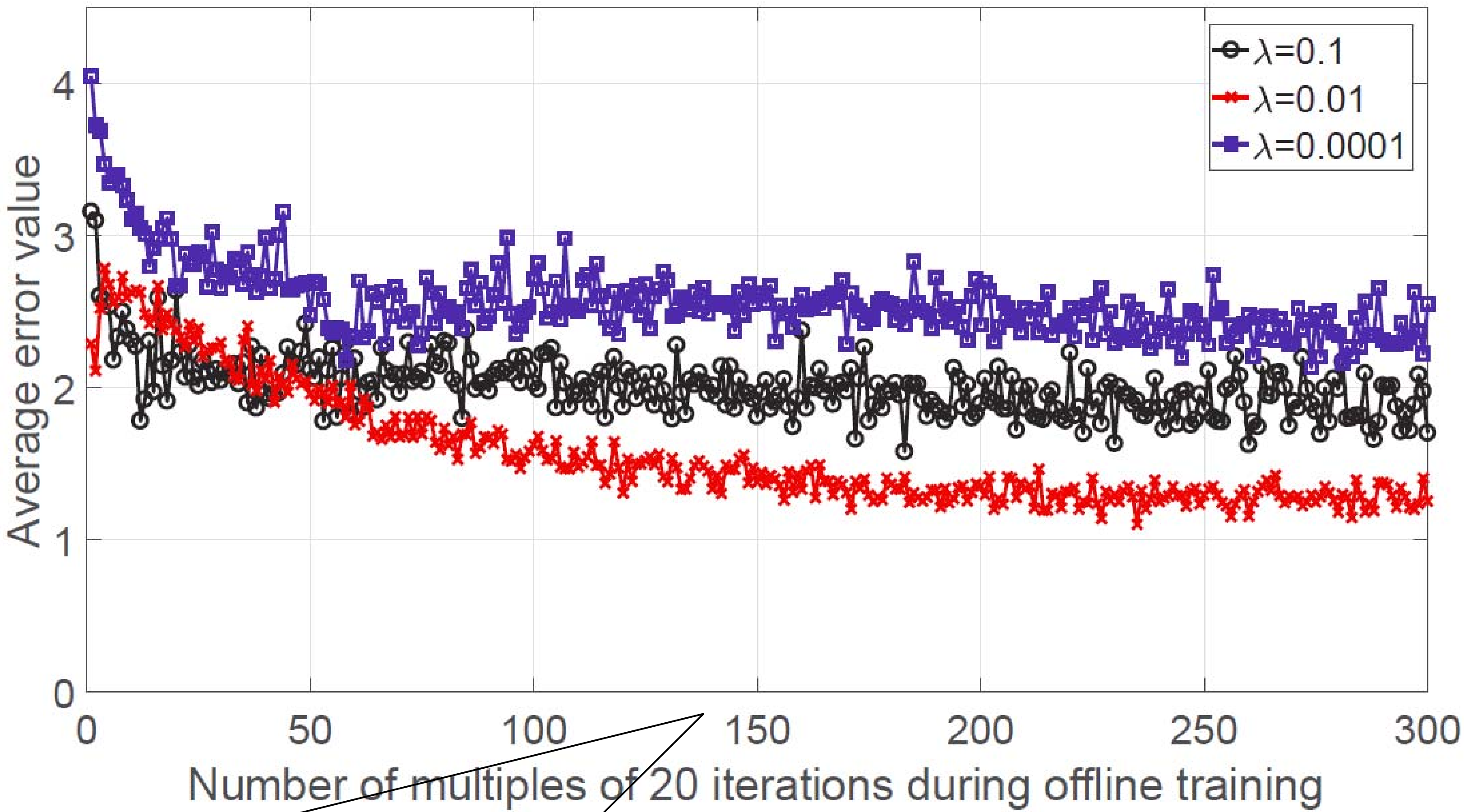
Simulation Results



Simulation Results



Simulation Results



Convergence depends on learning rate (0.01 is ideal for this case)

Other UAV Comm. Approaches

- UAVs as backhaul (see U. Challita and W. Saad, GLOBECOM 2017)
- More on machine learning (see M. Chen, W. Saad, et al., GLOBECOM 2017)
- UAVs as relay stations (see works by L .Swindelhurst et al. and R. Zhang et al.)
- Cyclical resource allocation with optimal deployment of UAVs as relays (see works by Y. Zeng and R. Zhang)
- Deployment within a cloud radio access network and related environments (see Yanikomeroglu et al.)
- Channel modeling, localization, tracking, public safety, and related ideas (see works by I. Guvenc et al.)

Part V – Security

CPS Security of UAVs

- UAVs are essentially **cyber-physical systems**
  - **Cyber vs. Physical:** the physical world follows (typically) laws of nature or control-theoretic models, which have different constraints and time scales compared to cyber features
  - **Human-in the loop:** man meets machine (UAV)
- CPS nature brings cyber and physical vulnerabilities
- As UAVs become more prevalent, they will face more and more security challenges
  - Autonomy is both a blessing and a curse
  - **Let's see an example security problem**

Delivery Drones

- Drones will be used in the real-world for delivering goods or to deliver rescue mission items

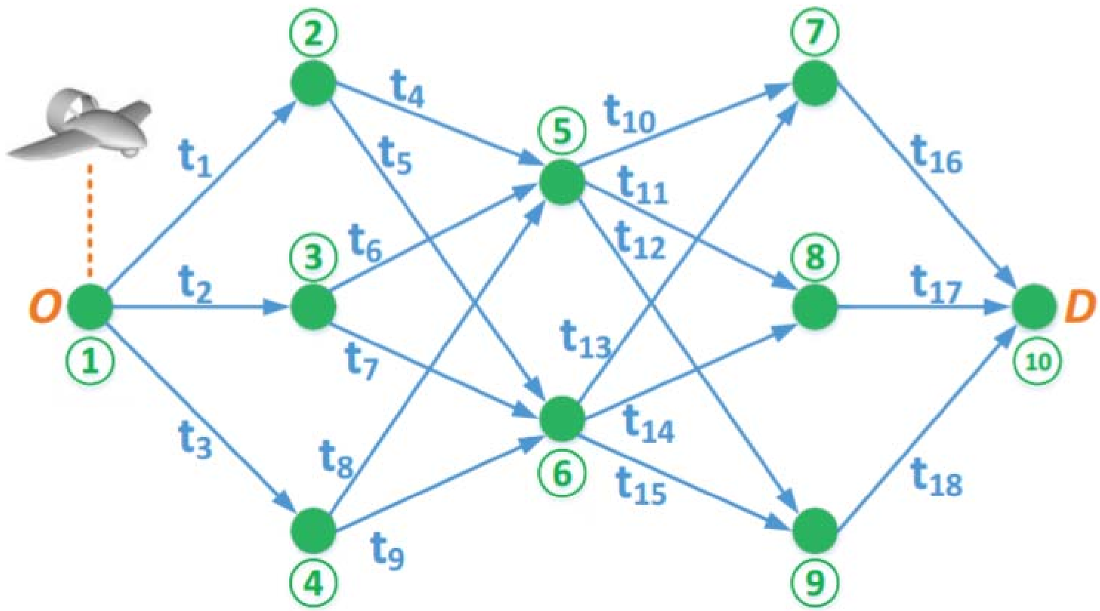
Security of Delivery Drones

- Delivery drones are prone to a variety of cyber-physical security threats
  - Cyber attacks to hack the cyber/wireless system and re-route the drone or to jam its communication
  - Commercial drones will be in the range of civilian-owned **hunting rifles** that can be used for physical attacks
- In such scenarios, humans will be in the loop!
  - Attackers will likely be humans (e.g., choose a high point to shoot the drone or jam its link in line-of-sight)
  - Vendors who own the drones will have stringent delivery times especially for **medical** delivery (framing effects!)

Basic System Model

- A vendor sends a delivery drone from an origin *O* to a destination *D*
  - In an ideal world, vendor always chooses shortest path
- Presence of adversary
  - Attackers can interdict the drone at several threat points such as high buildings or hills to cause physical or cyber damage
  - A destroyed drone must be re-sent by the vendor, leading to increased delivery times and economic losses
- The system can be modeled as a graph

Basic System Model



- The vendor is *an evader* wants to minimize expected delivery time by choosing an optimal path
- The attacker is *an interdictor* who chooses a location to attack the drone and maximize the delivery time
- ***Natural zero-sum network interdiction game***

Game Formulation

- Two-player zero-sum game in which both vendor and attacker want to randomize over their strategies
  - Defender mixed-strategy vector $\boldsymbol{y} \triangleq [y_1, y_2, \ldots, y_H]^T$
  - Attacker mixed-strategy vector $\boldsymbol{x} \triangleq [x_1, x_2, \ldots, x_N]^T$
- Attack at location *n* will be successful with probability p_n
- The expected delivery time will be:

$$T = \sum_{h \in \mathcal{H}} \sum_{n \in \mathcal{N}} y_h x_n [l_{hn} p_n f^h(n) + f^h(D)].$$

  - $f^h(.)$ is a distance function
  - T depends on various parameters

Game Formulation

- Vendor problem

$$T^* = \min_{\boldsymbol{y}} \max_{\boldsymbol{x}} \boldsymbol{y}^T \boldsymbol{M} \boldsymbol{x},$$

$$\text{s.t.} \quad \mathbf{1}_N \boldsymbol{x} = 1,\ \mathbf{1}_H \boldsymbol{y} = 1,$$

$$\boldsymbol{x} \geq 0,\ \boldsymbol{y} \geq 0,$$

- Adversary problem

$$\max_{\boldsymbol{x} \in \mathcal{X}} \min_{\boldsymbol{y} \in \mathcal{Y}} \boldsymbol{y}^T \boldsymbol{M} \boldsymbol{x}$$

- As a zero-sum game, it can be transformed into two linear programs that can be easily solved
- Game admits a Nash (saddle-point) equilibrium
- There may be more than one equilibrium, but they are all interchangeable yielding the same delivery time
- ***But what about the human perceptions?***

Expected Utility Theory

- Conventionally, the Nash equilibrium is found under expected utility theory (EUT) considerations
  - Presumes that players act **rationally**
  - The players optimize the expected value over their mixed strategies, i.e.,

$$U_k^{\mathrm{EUT}}(\boldsymbol{p}) = \sum_{\boldsymbol{a} \in \mathcal{A}} \left(\prod_{l=1}^{K} p_l(a_l) \right) u_k(a_k, \boldsymbol{a}_{-k})$$

  - Caveat: in practice, it has been empirically shown that when users are faced with uncertainty, they act **irrationally**

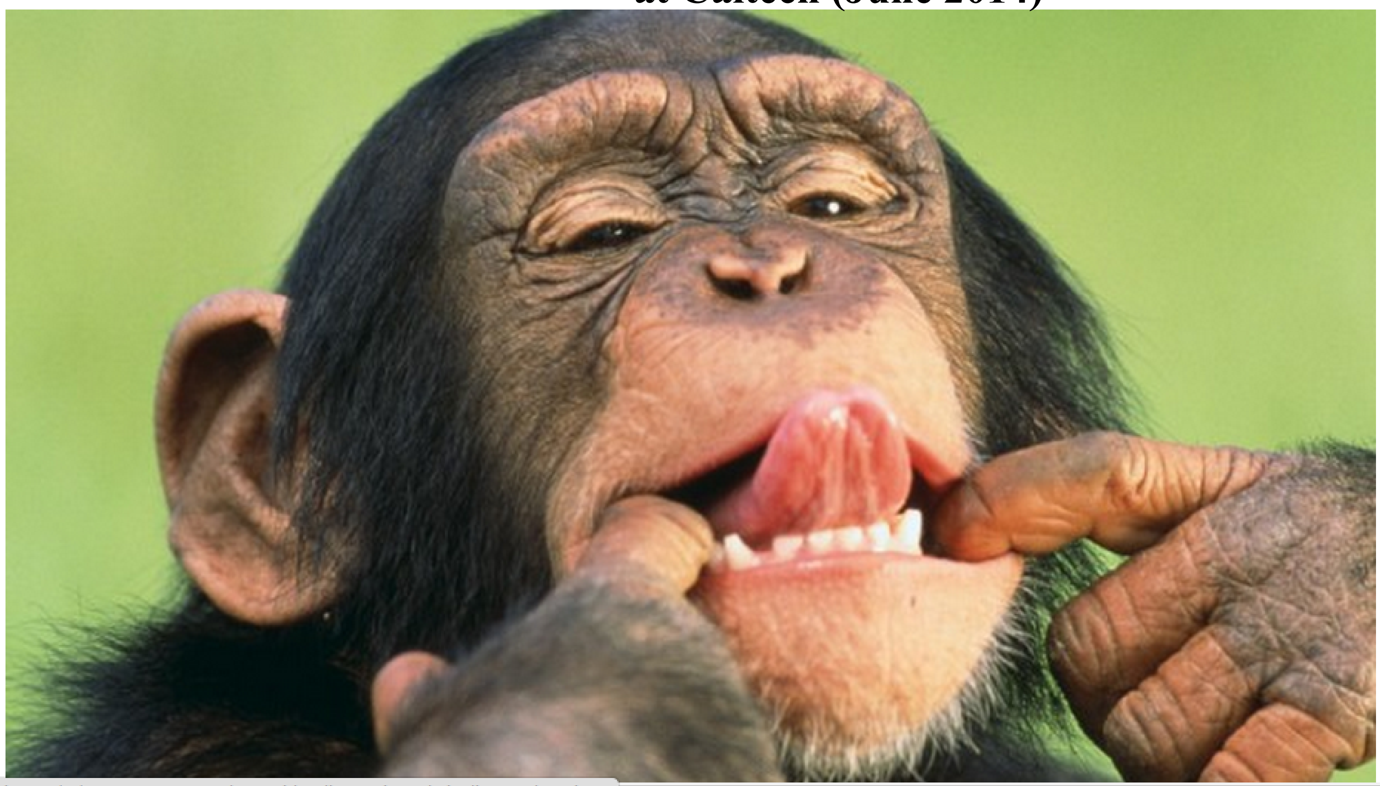
Are humans really rational?

- Example: In the real-world, security problems often involve human decision makers at both sides of the aisle (attack/defense)
  - **Human in the loop**

Chimps Outsmart Humans When It Comes To Game Theory

June 6, 2014

Source: Study between Kyoto University and game theorists at Caltech (June 2014)



How to capture such irrationality?

Prospect Theory

- Lottery example
  - Risk impacts how players weigh certain outcome
  - Uncertainty can lead players to deviate from the rational norms of EUT
  - Subjective perception on losses/gains
  - In CPS and UAV, many human players are in the loop and will have subjective perceptions on the various performance and network measures
- Solution: **Prospect theory!**

Example

- The preferred choice between a pair (or more) of uncertain alternatives is determined by:
  - Value of the alternatives (as is customary) but also..
  - How those choices are stated!
- **Gain Scenario:** You average monthly bill is now $450 a month. Under our new smart system your bill will now show a debit of $500 a month. Also, you may choose:
  - A) 50% chance of a $100 credit if you join our new wireless pricing system
  - B) 100% chance of a credit of $50 that will keep your bill the same

Example

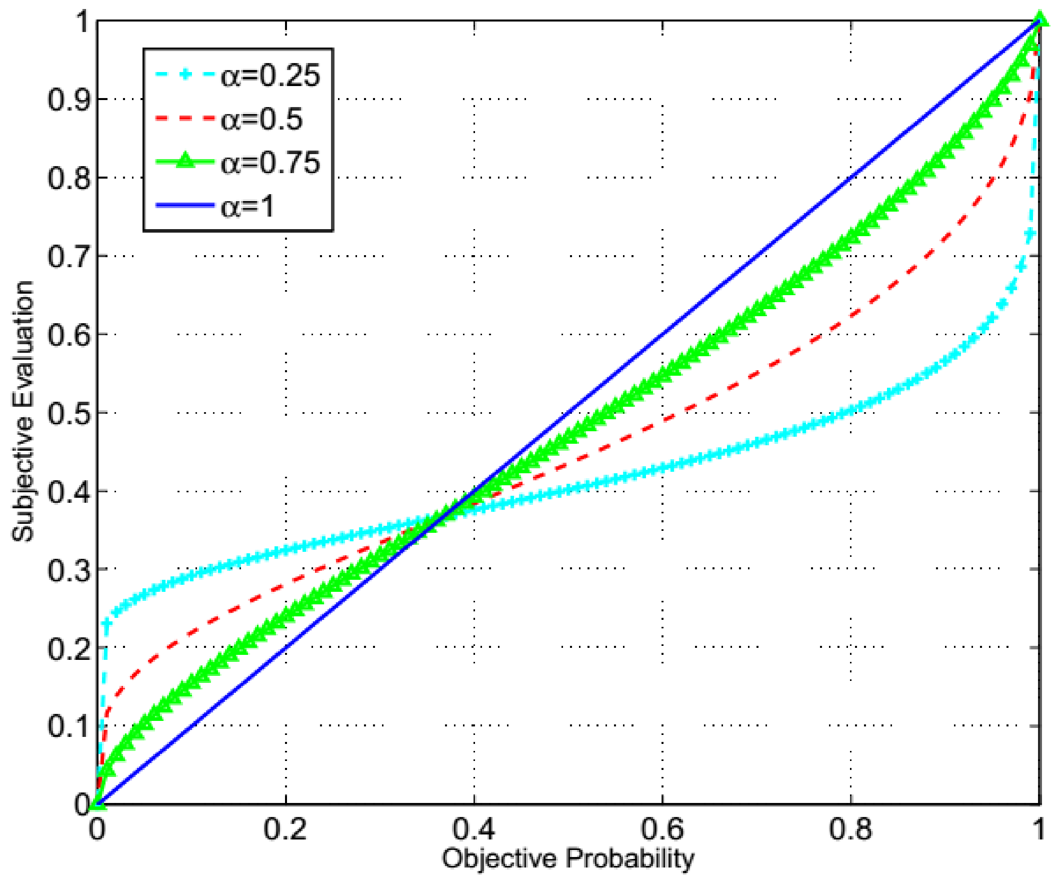
- **Loss Scenario:** Your average monthly bill is now $450 a month. Under our new smart system your bill will now show a debit of $400 a month. Also, you may choose:
  - C) 50% chance of a bill for $100 if you join our system
  - D) 100% chance of a bill of $50 that will keep your bill the same
- A) and C) are identical, while B) and D) are identical
- Prospect theory found that people will always prefer B) to A) and C) to D)
  - A certain gain is preferred to an uncertain double gain!
  - An uncertain loss is preferred to a certain, smaller loss!

Prospect Theory

- Prospect theory
  - Introduced by Kahneman and Tversky (1979)
  - Won them the **Nobel prize** in 2002
  - Cognitive psychology basis for analyzing human errors and deviations from rational behavior
- Two important observations:
  - **Weighting effect:** Players can subjectively weight outcomes that are uncertain or risky
  - **Framing effect:** Players may evaluate their utilities as gains/losses with respect to a reference point

Illustrating the Weighting Effect

- Weighting effect
  - Prelec function
  - Outcomes are weighted differently
- Weighting applies to probabilistic outcomes (e.g. mixed strategies)



Prospect Theory

- With weighting, the players now optimize:

$$U_k^{\mathrm{PT}}(\boldsymbol{p}) = \sum_{\boldsymbol{a} \in \mathcal{A}} \left(p_k(a_k) \prod_{l \in \mathcal{K} \setminus \{k\}}^{K} w(p_l(a_l)) \right) u_k(a_k, \boldsymbol{a}_{-k})$$

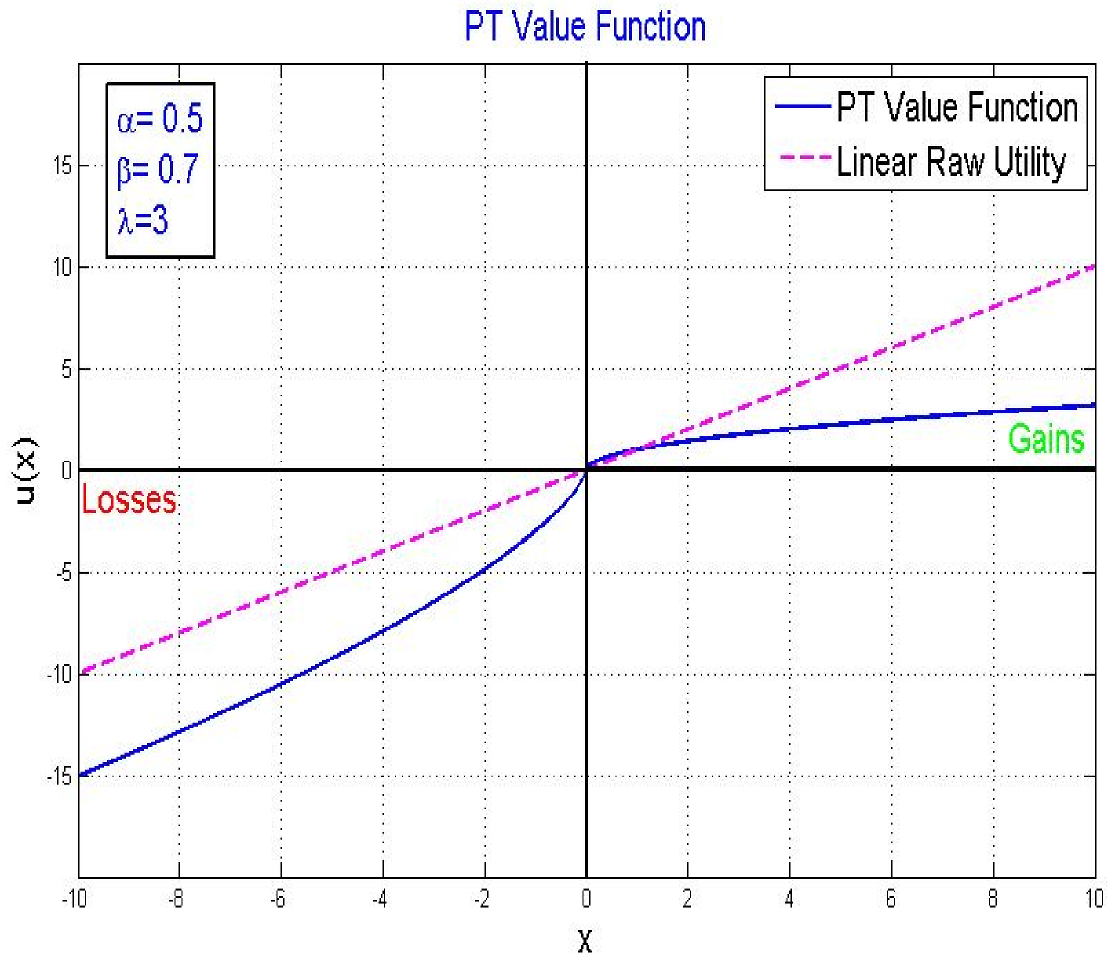
Weighting effect, Prelec function:

$$w(\sigma) = \exp(-(-\ln \sigma)^{\alpha}), \; 0 < \alpha \leq 1$$

- Framing effect
  - Each player will "frame" its gains/losses with respect to a reference point
  - Losses loom larger than gains

Prospect Theory

- Concave in gains
- Convex in losses
- Steeper slope for losses as opposed to gains
- Risk averse in gains, risk seeking in losses



Prospect Theory

- Framing effects
  - The following framing function has been proposed:

$$V(\boldsymbol{X}) = \begin{cases} X^{\gamma} & \text{if } X > 0, \\ (-\lambda)(-X)^{\beta} & \text{if } X < 0, \end{cases}$$

where $0 < \beta, \gamma \leq 1$ and $\lambda \geq 1$.

- Suitable applications for PT?
  - When humans are making decisions (CPS with human-in-the loop, smart grid, pricing , human hackers, security)
  - UAV security is a prime example, given the impact of UAV performance on owners/humans

Prospect Theory in UAV

- The standard formulation does not account for the presence of humans in the loop that are facing uncertainty
- **Uncertainty:** perceptions of both attacker and vendor on the probability of successful attack (weighting effect)
- **Framing:** subjective perception on the delivery time with respect to a reference point
  - Even the smallest of delays can be catastrophic
  - For rescue situations, survival is at stake
  - For Amazon, reputation can be damaged

Prospect Theory

- Subjective, PT-based utility

$$V_z(T)=\sum_{h\in\mathcal{H}}\sum_{n\in\mathcal{N}} y_h x_n \left[v_z\left(l_{hn}\omega_z(p_n)f^h(n)+f^h(D)-R_z\right)\right].$$

Framing function

Weighting

Reference point

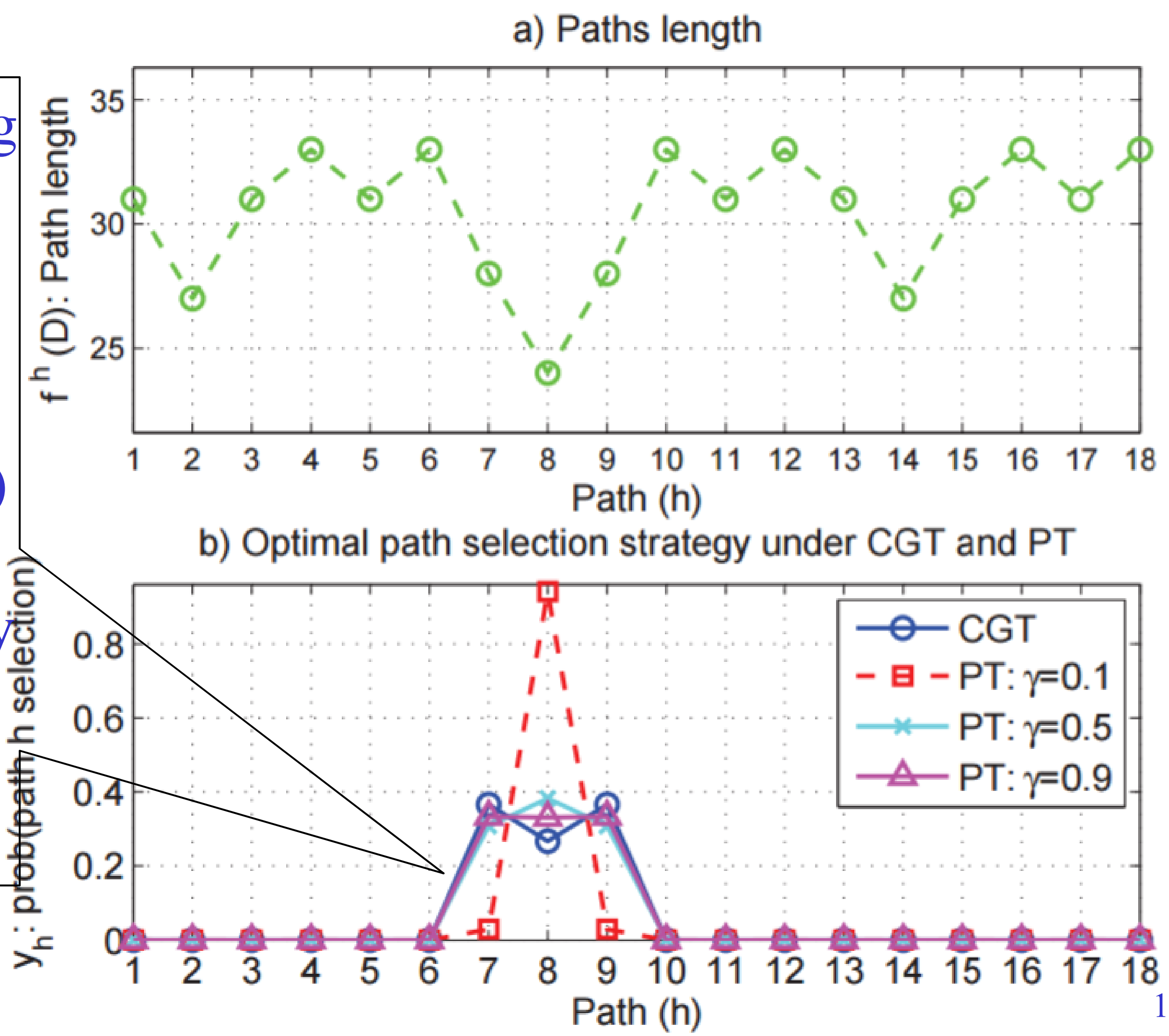
- The game is no longer zero-sum
- We consider max-min/min-max strategies

$$\min_{\boldsymbol{y}\in\boldsymbol{\mathcal{Y}}}\max_{\boldsymbol{x}\in\boldsymbol{\mathcal{X}}} \boldsymbol{y}^T \boldsymbol{M}^{U,\mathrm{PT}}\boldsymbol{x}, \quad \max_{\boldsymbol{x}\in\boldsymbol{\mathcal{X}}}\min_{\boldsymbol{y}\in\boldsymbol{\mathcal{Y}}} \boldsymbol{y}^T \boldsymbol{M}^{A,\mathrm{PT}}\boldsymbol{x}$$

- Ongoing work to characterize equilibria under PT

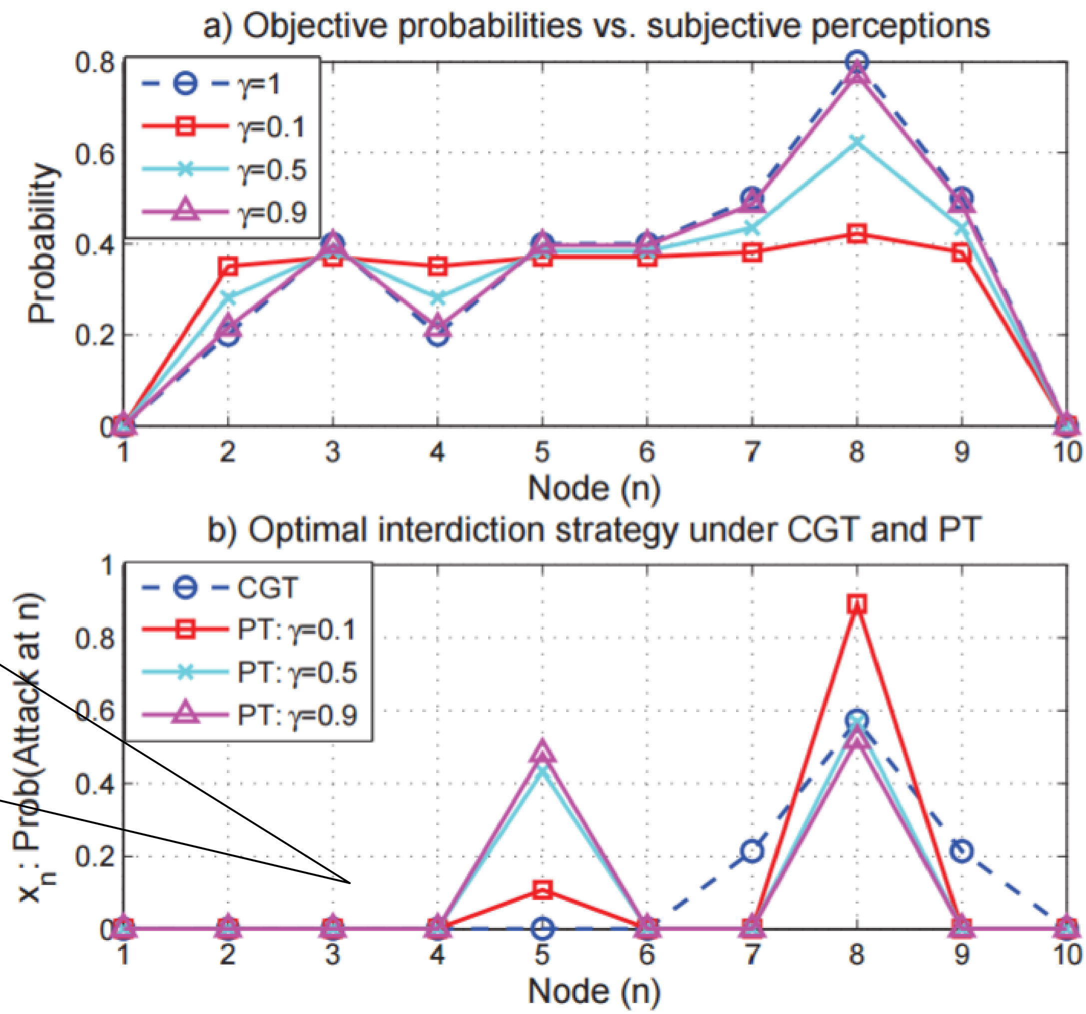
Simulation results (1)

Due to the weighting effect the vendor will still choose the shortest path despite being very risky ($p_n = 0.8$) This choice becomes more likely as the vendor becomes more irrational

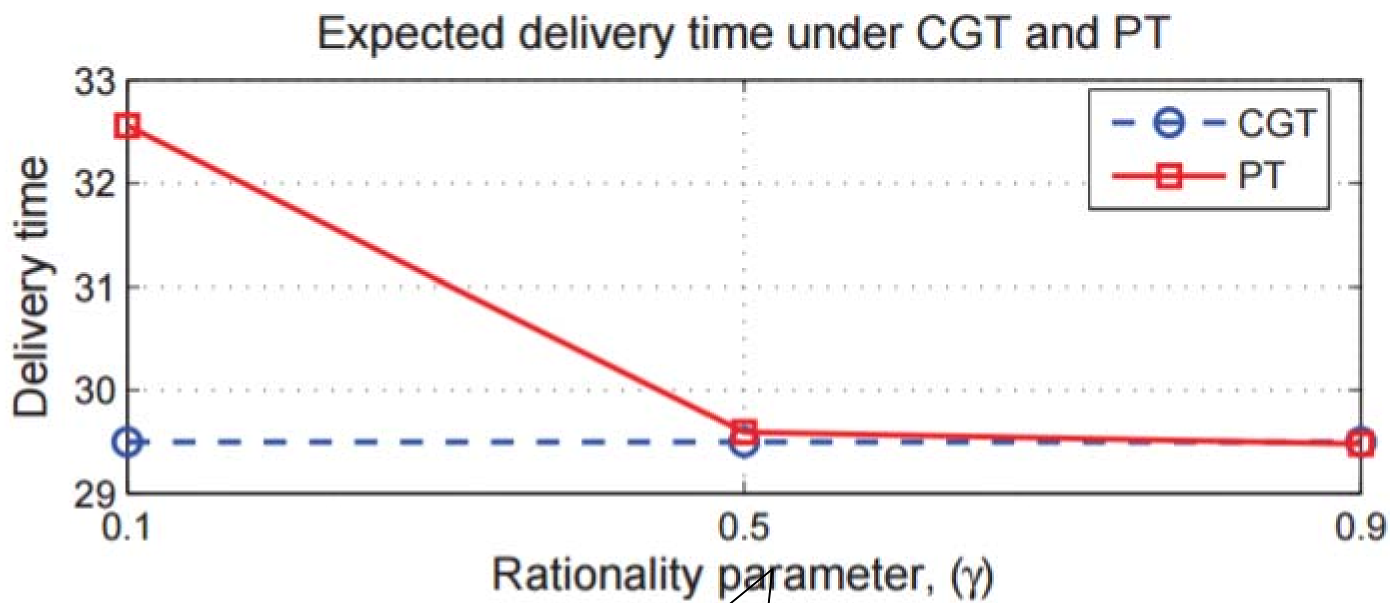


Simulation results (2)

Due to the weighting effect, the attacker focuses more on nodes 5 and 8 which are part of the shortest path



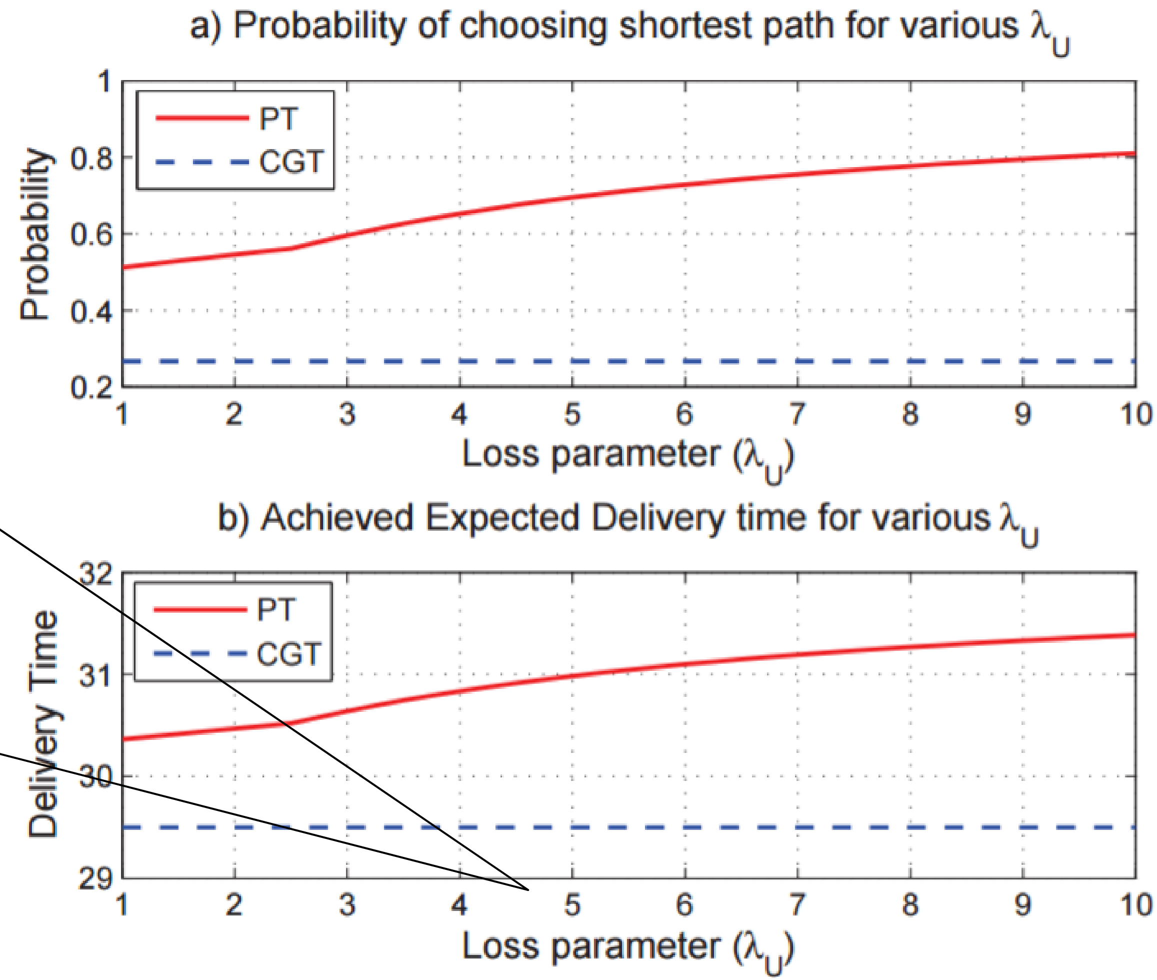
Simulation results (3)



Delivery time is increased by almost 10% not accounting for time to re-load and re-ship

Simulation results (4)

As the loss parameter increases the vendor exaggerates losses and thus starts choosing more risky paths to meet delivery time which, in turn, yields to a reverse effect!!!



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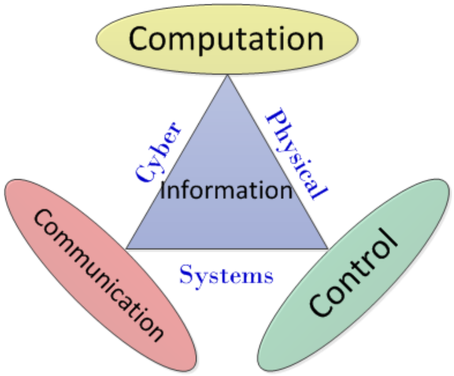
Conclusions

- UAVs provide with many new opportunities to improve wireless communications
- The **Internet of Flying Things** will be upcoming and we must be “analytically” ready
- Fundamental results on performance are needed
- Self-organization in terms of resources, network topology, access modes, security, etc.
  - Machine learning, game theory and related techniques
- Human-in-the-loop: bounded rationality
- **Ubiquitous wireless connectivity from the sky!**

Finally....



Thank You

Questions?

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