“UAV-Assisted Wireless Networks Using Machine Learning”

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Outline

- Introduction
- UAV-Assisted Wireless Networks: The Concept and Challenges
- Use Case Scenarios
  - Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks
  - Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing
  - Data Freshness and Energy-Efficient UAV Navigation Optimization: A Deep Reinforcement Learning Approach
- Concluding Remarks

Introduction

- Fifth-generation (5G) and beyond communications are mainly characterized by
  1) massive connectivity,
  2) ultra-reliability and low latency, and
  3) increased throughput.
- Satisfying these objectives in conjunction with the rapid growth of the Internet of Things (IoT) applications represents a challenging task, especially in highly dynamic and heterogeneous environments.
- A promising approach is to adopt unmanned aerial vehicles (UAVs) as aerial user equipments (UEs) or flying base stations (BSs).

Image Source: https://www.netscout.com/solutions/5g

Bithas, P.S.; Michailidis, E.T.; Nomikos, N.; Vouyioukas, D.; Kanatas, A.G. A Survey on Machine-Learning Techniques for UAV-Based Communications. *Sensors* **2019**, *19*, 5170

Introduction: Drawback of Current Communication System?

- The current wireless communication system fully depends on the infrastructure in order to provide services to mobile users. However, the deployment and operational cost of the infrastructure are high.

- Actually, mobile users can not get any services when infrastructure collapses because of the natural disasters.

- Moreover, users especially in the mountain areas, countryside and deep sea also can get internet access because it is difficult and not possible to deploy infrastructure for wireless communication.

Introduction: Drawback of Current Communication System?

Only 63.2% of world population can get internet access in till Oct, 2020.
So, how about the remaining 36.8 % ????

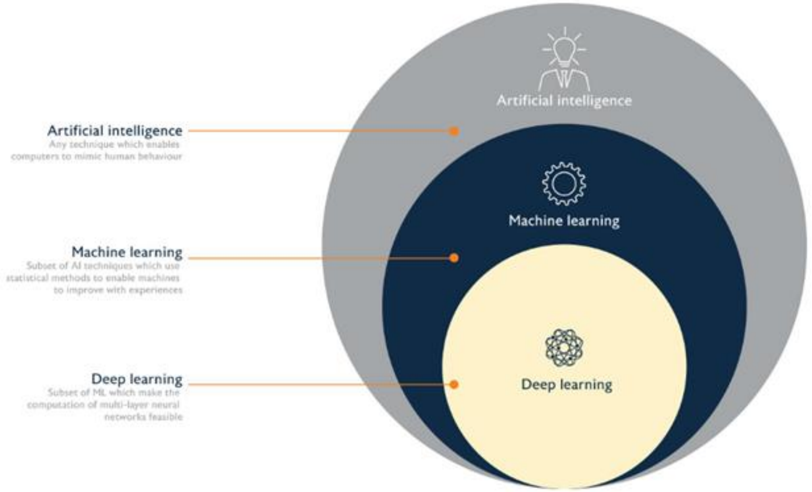
WORLD INTERNET USAGE AND POPULATION STATISTICS
2020 Year-Q3 Estimates

World Regions	Population (2020 Est.)	Population % of World	Internet Users 30 Sept 2020	Penetration Rate (% Pop.)	Growth 2000-2020	Internet World %
Africa	1,340,598,447	17.2 %	631,940,772	47.1 %	13,898 %	12.8 %
Asia	4,294,516,659	55.1 %	2,555,636,255	59.5 %	2,136 %	51.8 %
Europe	834,995,197	10.7 %	727,848,547	87.2 %	593 %	14.8 %
Latin America / Caribbean	654,287,232	8.4 %	467,817,332	71.5 %	2,489 %	9.5 %
Middle East	260,991,690	3.3 %	184,856,813	70.8 %	5,527 %	3.7 %
North America	368,869,647	4.7 %	332,908,868	90.3 %	208 %	6.8 %
Oceania / Australia	42,690,838	0.5 %	28,917,600	67.7 %	279 %	0.6 %
WORLD TOTAL	7,796,949,710	100.0 %	4,929,926,187	63.2 %	1,266 %	100.0 %

Source: https://www.internetworldstats.com/stats.htm

Introduction: AI/ML

- In particular, UAV-based communications can improve the network performance in emergency situations by providing rapid service recovery and by offloading in extremely crowded scenarios.
- The integration of artificial intelligence (AI) and machine-learning (ML) techniques in wireless networks can leverage intelligence for addressing various issues.
- Thus, the combination of AI/ML and UAVs appears to be strongly correlated in different disciplines and applications and throughout the network layers, promising unprecedented performance gains and complexity reduction.



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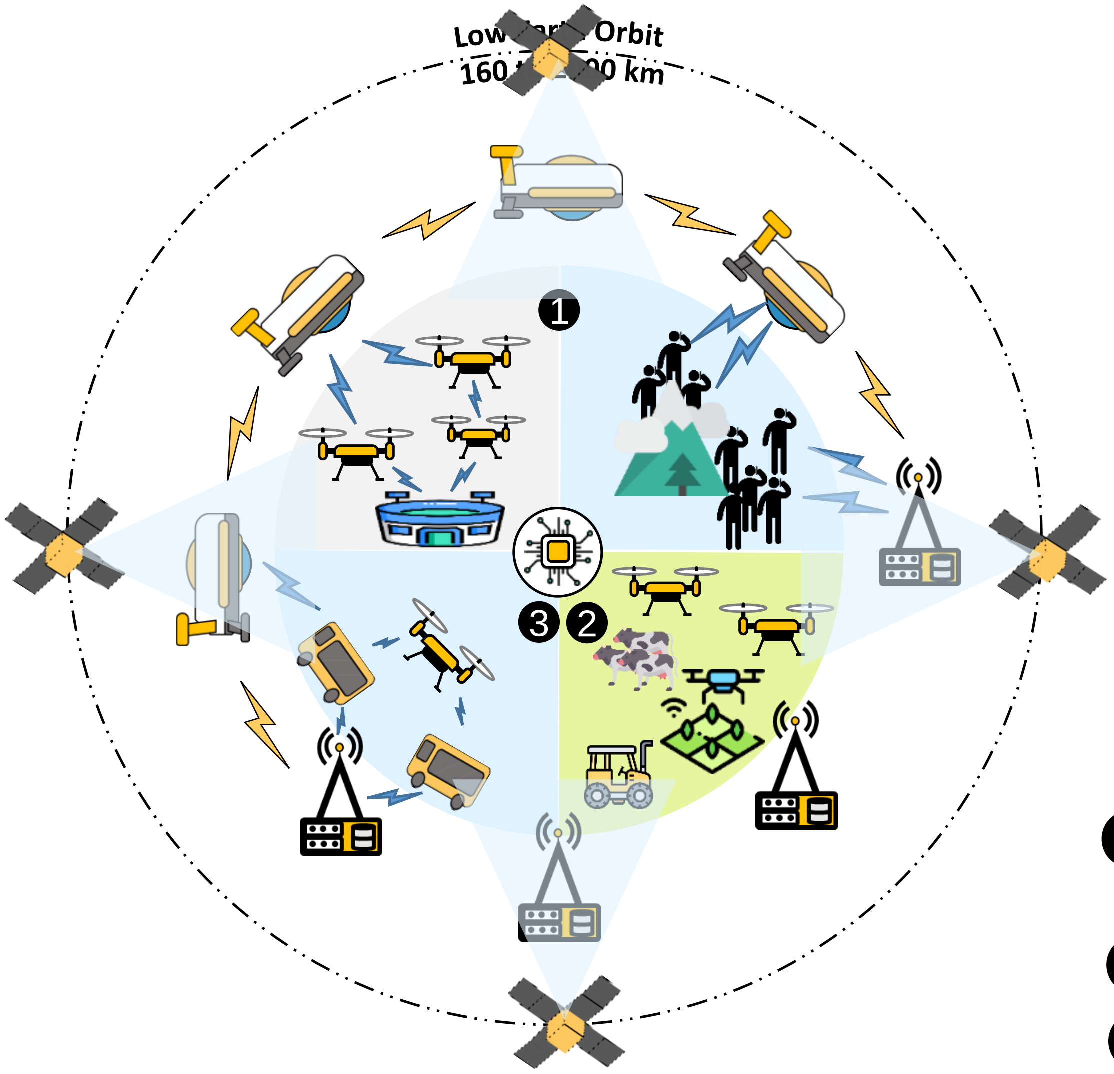
UAV-Assisted Wireless Networks: The Concept and Challenges

- Overview
- Ongoing Projects
- Types of UAVs
- Industrial Applications
- Challenges of UAV Deployment in Communication System
- Application of AI in UAV-based Communication

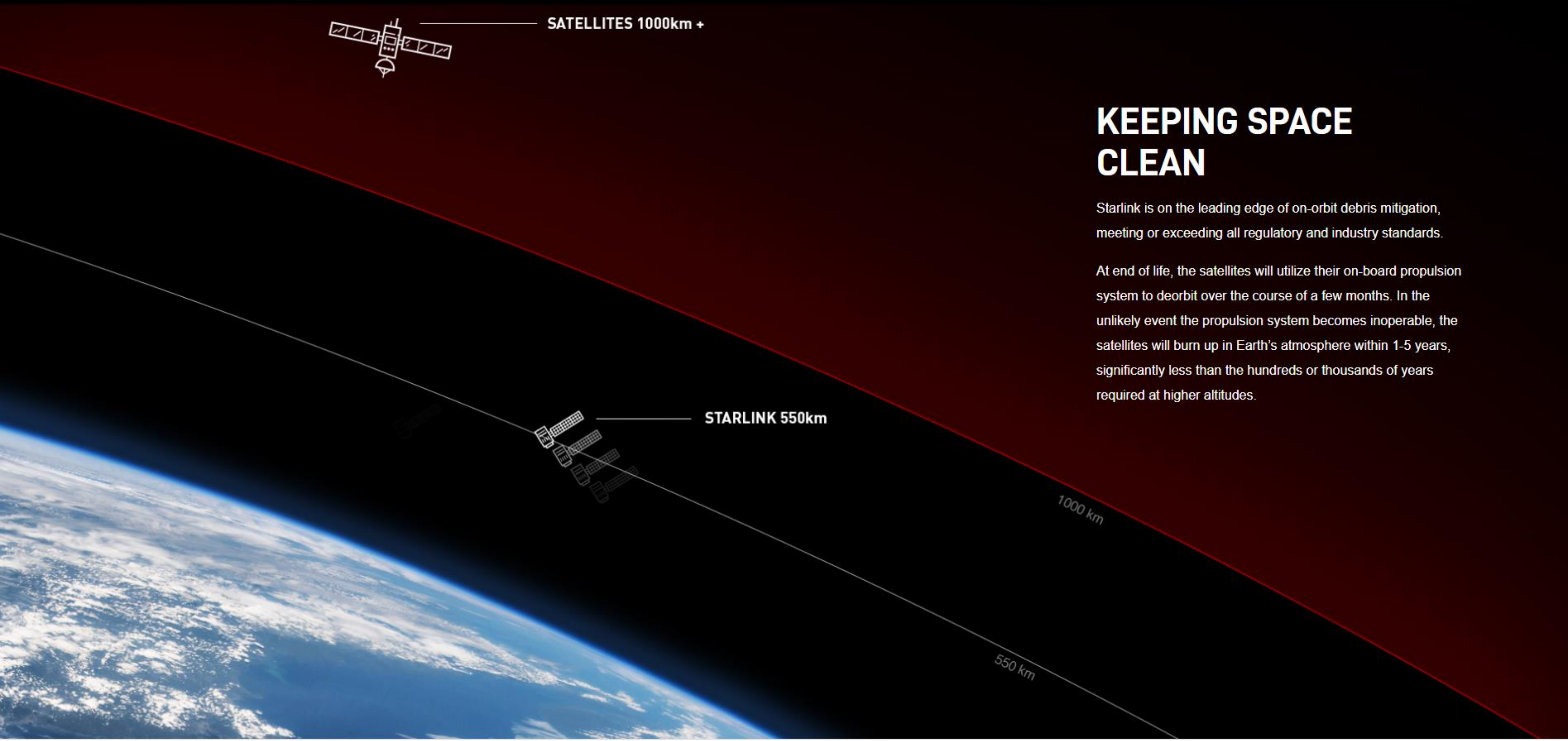
UAV-Assisted Wireless Networks Overview



- Cube satellite
- Airship
- Drone
- Base Station/ Small-cell Base Station/AP
- AI

1. On-demand unmanned aerial vehicle base station deployment
2. On demand data collection and analysis
3. Providing user-oriented services in next-generation mobile devices

Ongoing Projects: (SpaceX : Starlink Project)



https://www.starlink.com/

Ongoing Projects: (SpaceX : Starlink Project)

- Each satellite weighs approximately 573 pounds (260kg) and features a compact, flat-panel design that minimizes volume, allowing for a dense launch stack to take full advantage of the launch capabilities of SpaceX's Falcon 9 rocket.

- The satellites will be around 350 miles above earth.

https://www.starlink.com/

Ongoing Projects: (SpaceX : Starlink Project)

How fast will Starlink internet speeds be like?

- The latency should be between 25ms and 35 ms. This is fast enough for most internet tasks, including gaming.
- Download speeds will be pretty quick, at about 1Gbps

How many satellites will be needed for the services?

Federal Communications Commission (FCC) allows to put 12,000 SpaceX satellites above the planet

When will Starlink internet be available?

Expected to lunch sometime in 2021

Ongoing Projects: (SpaceX : Starlink Project)

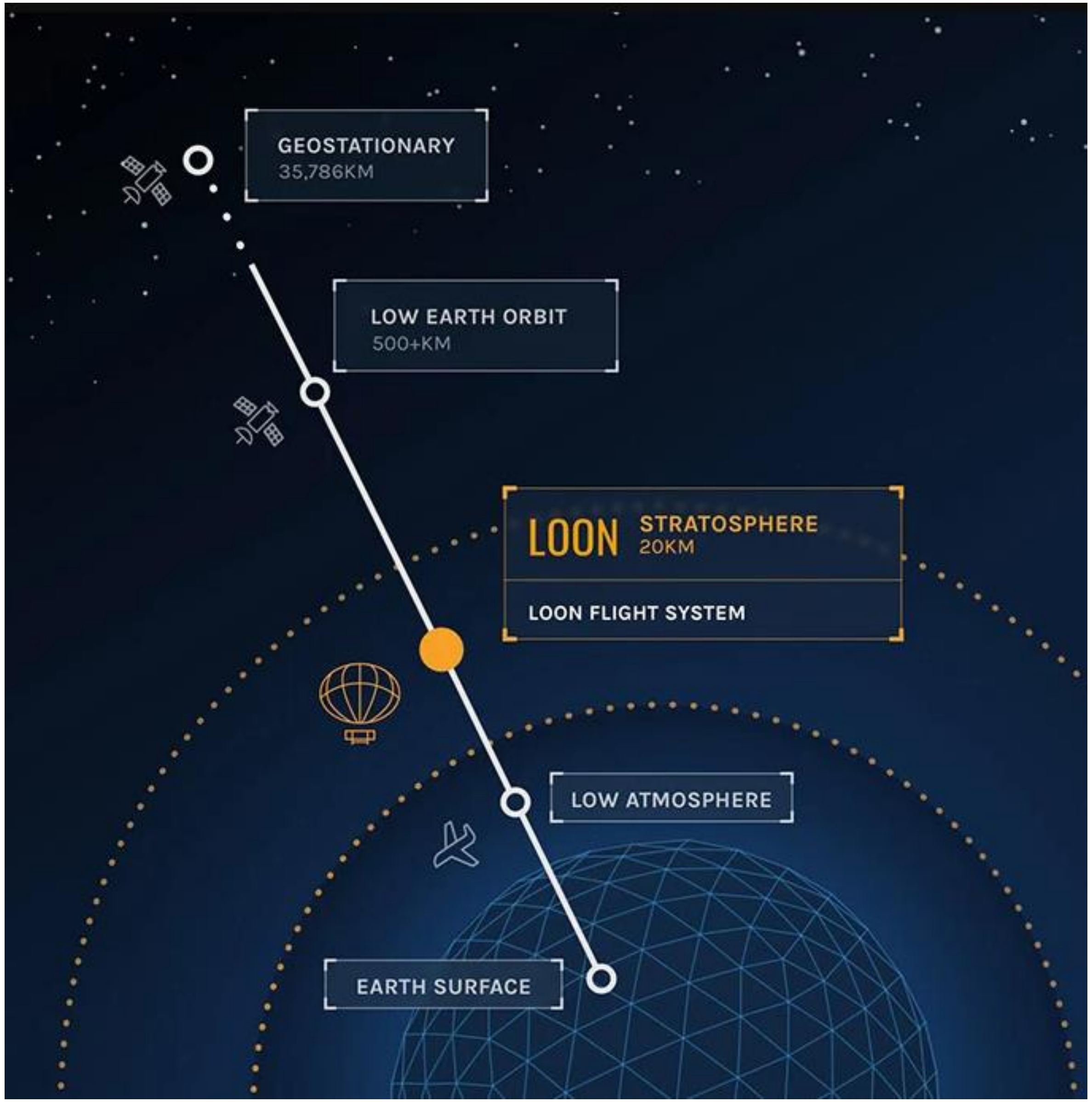
- Ku (12-18 GHz), Ka (26.5-40 GHz) and V (40-75 GHz) bands.
- V and Ku bands for network's users.
- V and Ka bands will be used to connect to gateways and for tracking, telemetry and control purpose.
  - Transmissions from satellite to user terminals: 10.7 – 12.7 GHz and 37.5 – 42.5 GHz
  - Satellite to gateway transmissions: 17.8 – 18.6 GHz and 18.8 – 19.3 GHz and 37.5 – 42.5 GHz
  - Transmissions from terminals to satellites: 14.0 – 14.5 GHz and 47.2 – 50.2 GHz and 50.4 – 51.4 GHz
  - Transmissions from gateways to satellites: 27.5 – 29.1 GHz and 29.5 – 30.0 GHz and 47.2 – 50.2 GHz and 50.4 – 51.4 GHz
  - Tracking, telemetry and control (downlink): 12.15 – 12.25 GHz and 18.55 – 18.60 GHz and 37.5 – 37.75 GHz
  - Tracking, telemetry and control (uplink): 13.85 – 14.00 GHz and 47.2 – 47.45 GHz

https://www.elonx.net/starlink-compendium/#:~:text=Here%20is%20a%20breakdown%20of,GHz%20and%2037.5%20%E2%80%93%2042.5%20GHz&text=Transmissions%20from%20gateways%20to%20satellites,GHz%20and%2050.4%20%E2%80%93%2051.4%20GHz

Goolge's Project Loon: A network of balloons travelling on the edge of space is designed to connect people in rural and remote areas, helping fill coverage gaps, and brining people back online after natural disasters.

Source: https://www.seminarsonly.com/computer%20science/project-loon-seminar-report-ppt.php

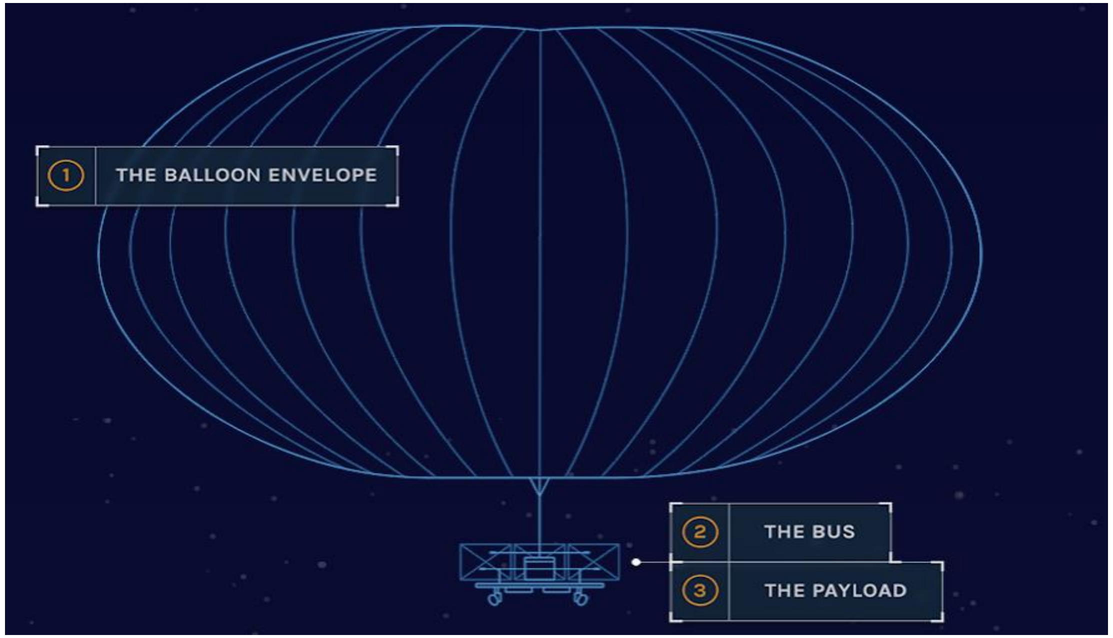
Ongoing Projects: Google's Project Loon (High Altitude Platform)



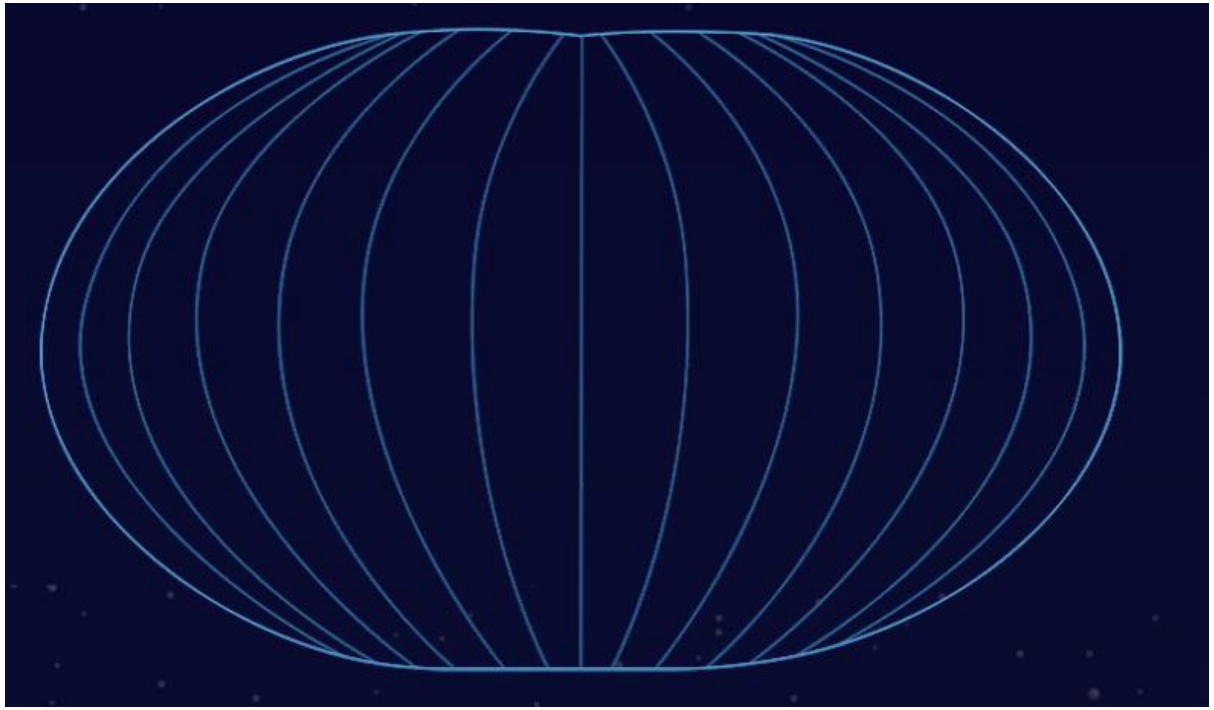
The Loon Flight System consists of three separate systems:

1. The balloon envelope
2. The bus
3. The payload

Together, they work seamlessly to provide lift, monitor flight telemetry, and provide connectivity.



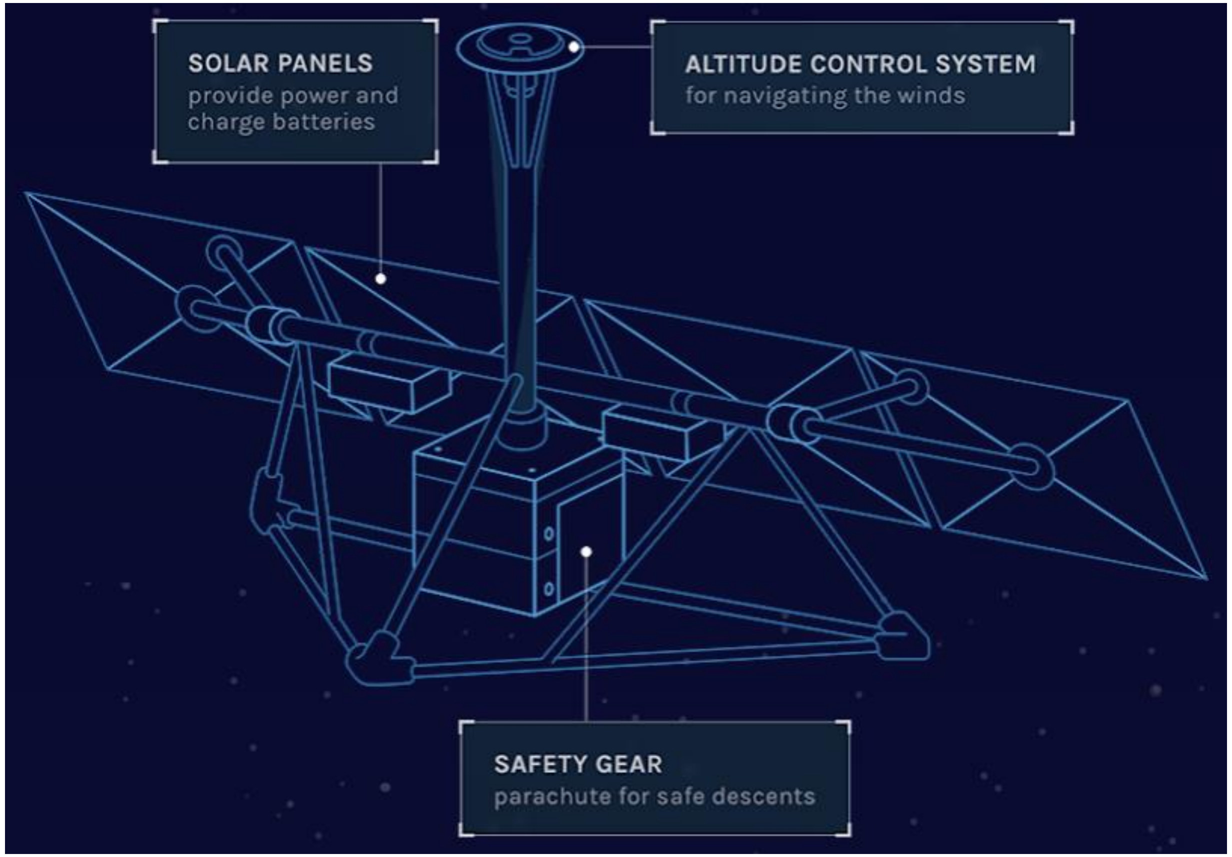
https://loon.com/technology/



Balloon Envelope

Made from polyethylene, each tennis-court-sized balloon envelope actually consists of a balloon inside of a balloon. A fixed amount of lift gas in the inner balloon keeps the system aloft. Adding or releasing outside air to the outer balloon changes density, allowing the system to ascend or descend when needed. Our balloons are built to last for hundreds of days before landing back on Earth in a controlled descent.

https://loon.com/technology/flight-systems/

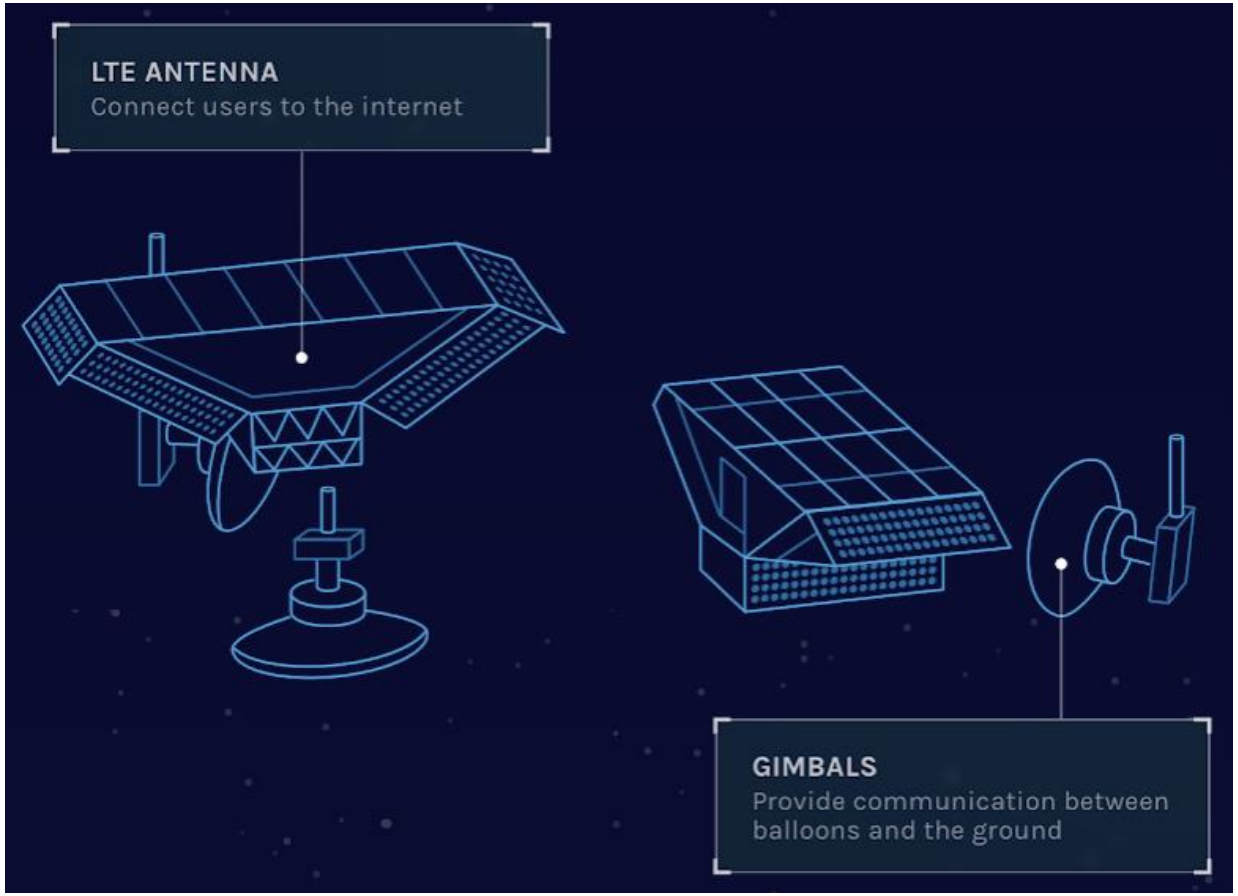


Bus

The bus consists of the hardware necessary for safe flight operations, including highly efficient solar panels that power the system, an altitude control system for navigation, and a parachute that deploys automatically to guide the balloon safely back to Earth after flight. For added safety, Loon includes redundant satellite communications links and transponders for constant visibility to air traffic control.

https://loon.com/technology/flight-systems/

Ongoing Projects: Google's Project Loon (High Altitude Platform)

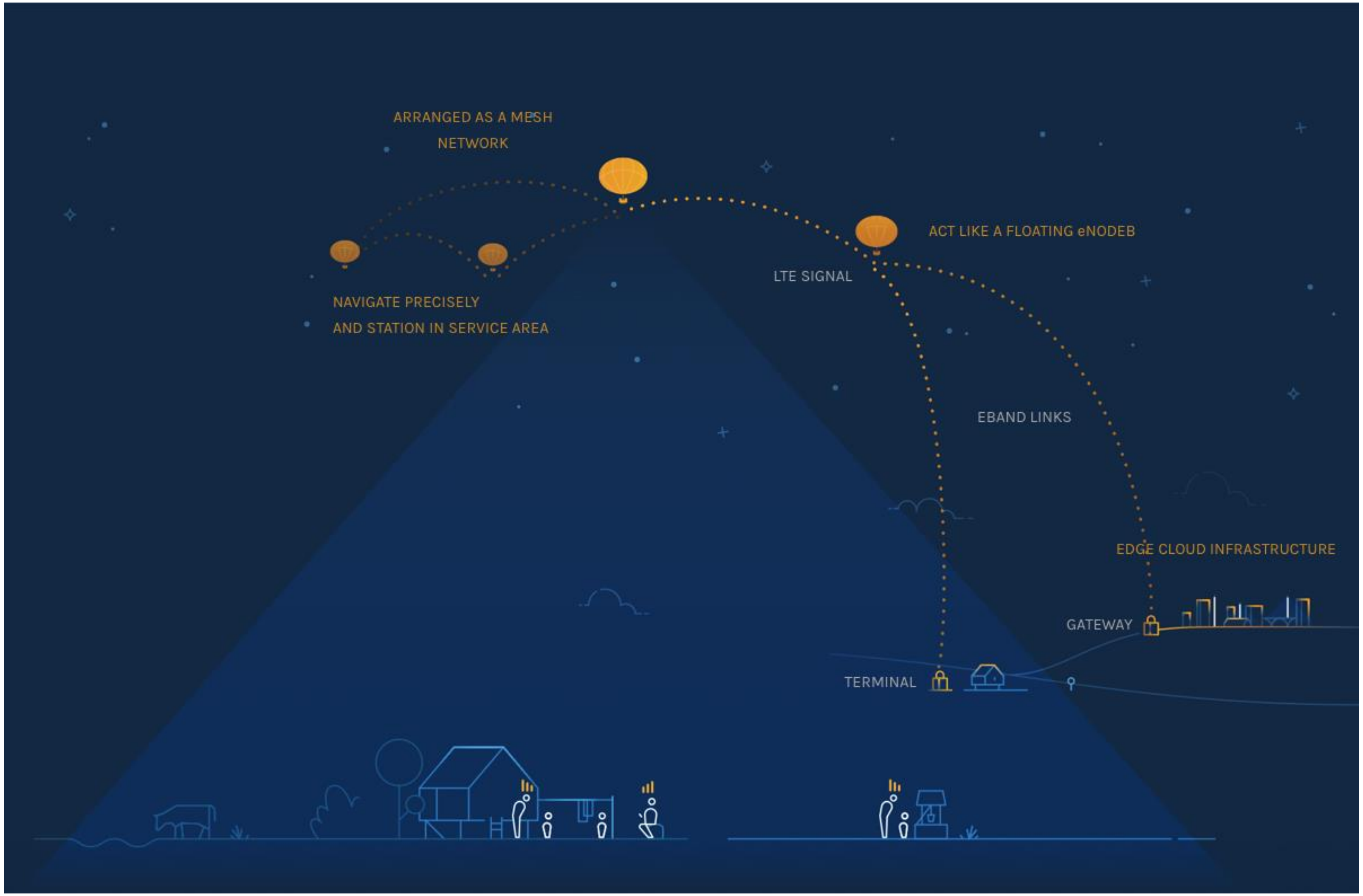


Payload

The payload consists of the communications equipment required to deliver connectivity, including the radio base station and antennas.

https://loon.com/technology/flight-systems/

Ongoing Projects: Google's Project Loon (High Altitude Platform)



HOW IT WORKS

- Loon integrates with mobile network operators' existing network infrastructure to extend their coverage.
- We maximize value by delivering seamless connectivity to subscribers through a unique solution of ground gateways, flight vehicles and software.

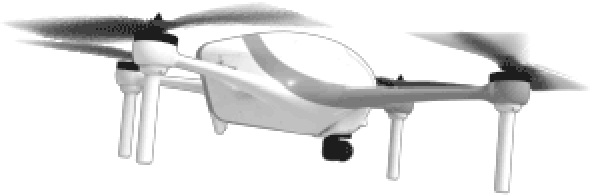
https://loon.com/technology/flight-systems/

What Is an Unmanned Aerial Vehicle (UAV)?

"UAV" refers specifically to aircraft that can be remotely piloted without requiring a human on-board to fly. While this term can be used accurately to describe drones in commercial or civilian use cases, it is most commonly used in reference to military applications.

Two types of UAVs

Fixed Wing UAV



Rotary Wing UAV

What is an Unmanned Aircraft Systems (UAS)?

"Unmanned aircraft systems" refers to the entire system required for advanced drone operations including the aircraft, ground control station, and communications system. UAS can either require a human pilot on the ground or be fully autonomous without need for a human. Any UAS includes a UAV as the aircraft component of the system.

https://percepto.co/what-are-the-differences-between-uav-uas-and-autonomous-drones/

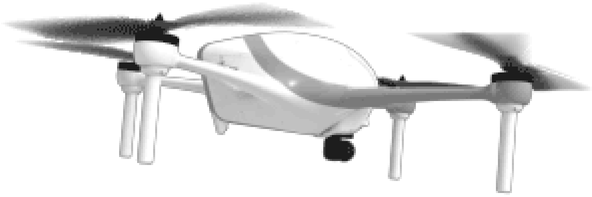
What is an Autonomous Drone?

The term "autonomous drone" describes a UAV that can operate without any human intervention. In other words, it can take off, carry out missions, and land completely autonomously.

An "autonomous drone" is a type of UAV, but a UAV is not necessarily an "autonomous drone". In the case of autonomous drones, communications management software coordinates missions and pilots the aircraft instead of a human. Because an "autonomous drone" is piloted by software instead of a human, an autonomous drone is part of a UAS by definition, as it requires a complete system to operate.

https://percepto.co/what-are-the-differences-between-uav-uas-and-autonomous-drones/

Types of UAVs: Automation VS Autonomy



Automation

The use or introduction of automatic equipment in a manufacturing or other process or facility.

How automated a drone is always comes down to how much automatic equipment is involved and how much manual intervention it requires. An automated drone follows orders about destination and route but cannot make decisions.

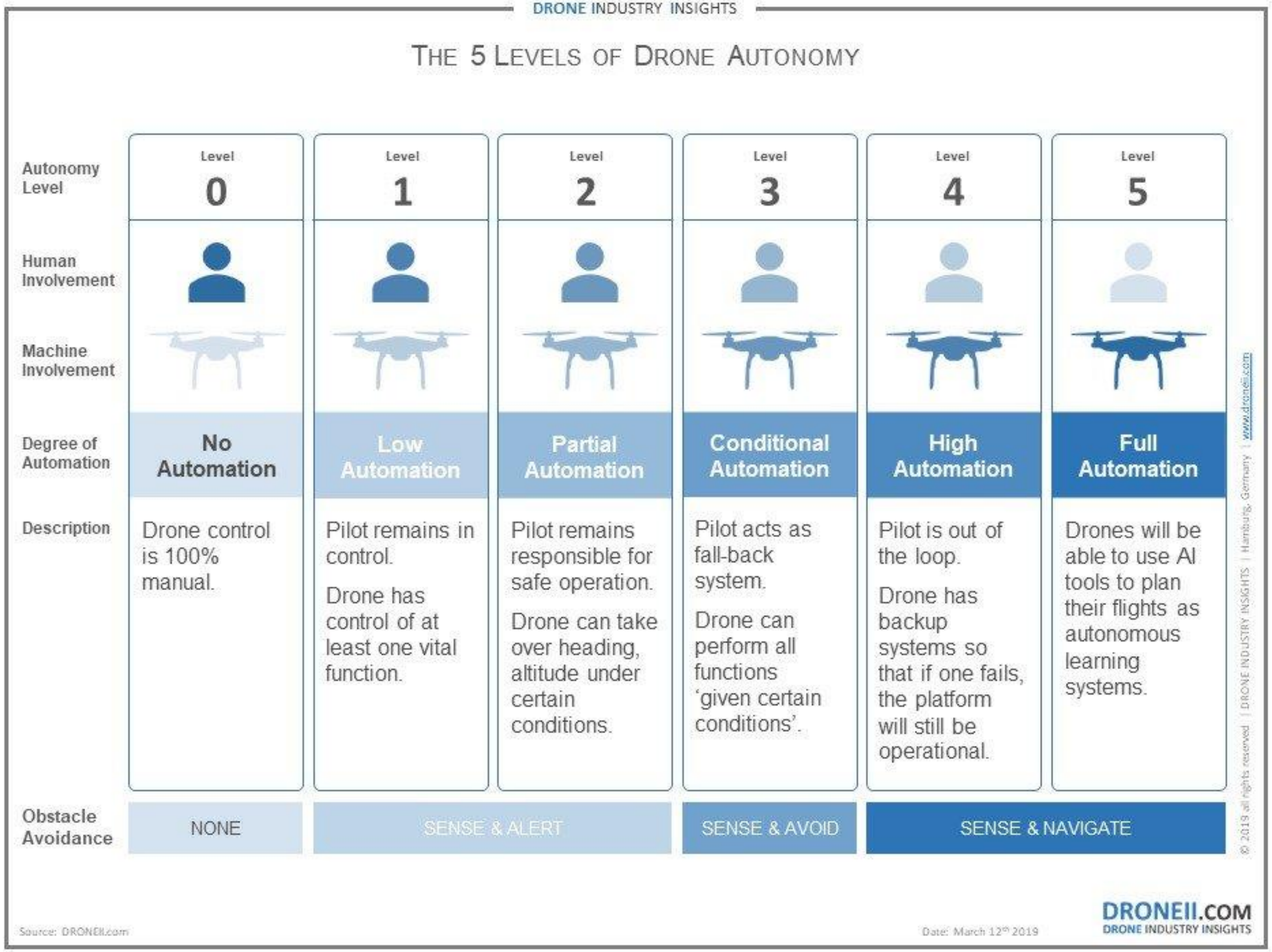
Autonomy

Freedom from external control or influence; independence.

How autonomous a drone is must always be a measurement of how independent the platform and its workflow are. A truly autonomous drone would *decide* on destination and route as well as control in the air.

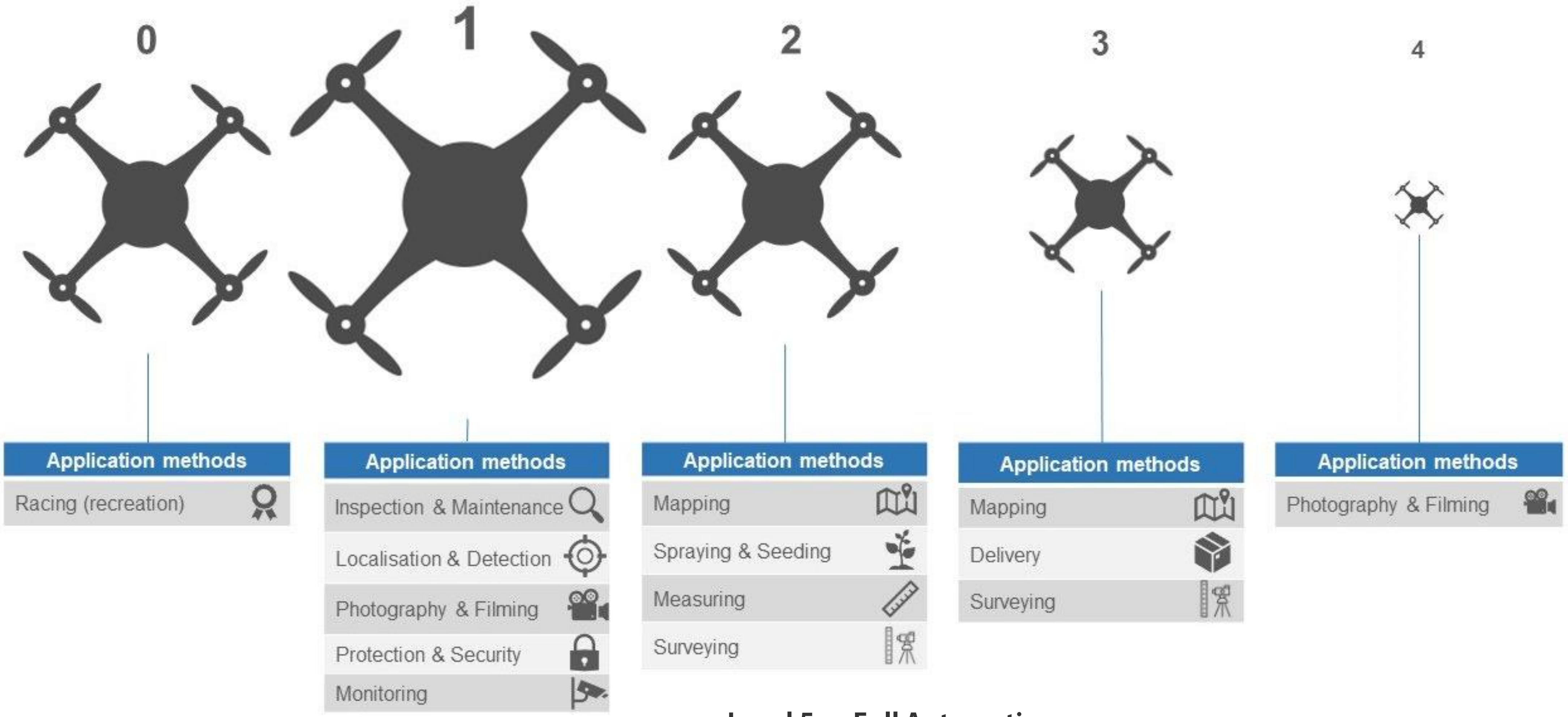
https://dronelife.com/2019/03/11/droneii-tech-talk-unraveling-5-levels-of-drone-autonomy/

Types of UAVs: Levels of Drone Autonomy



https://dronelife.com/2019/03/11/droneii-tech-talk-unraveling-5-levels-of-drone-autonomy/

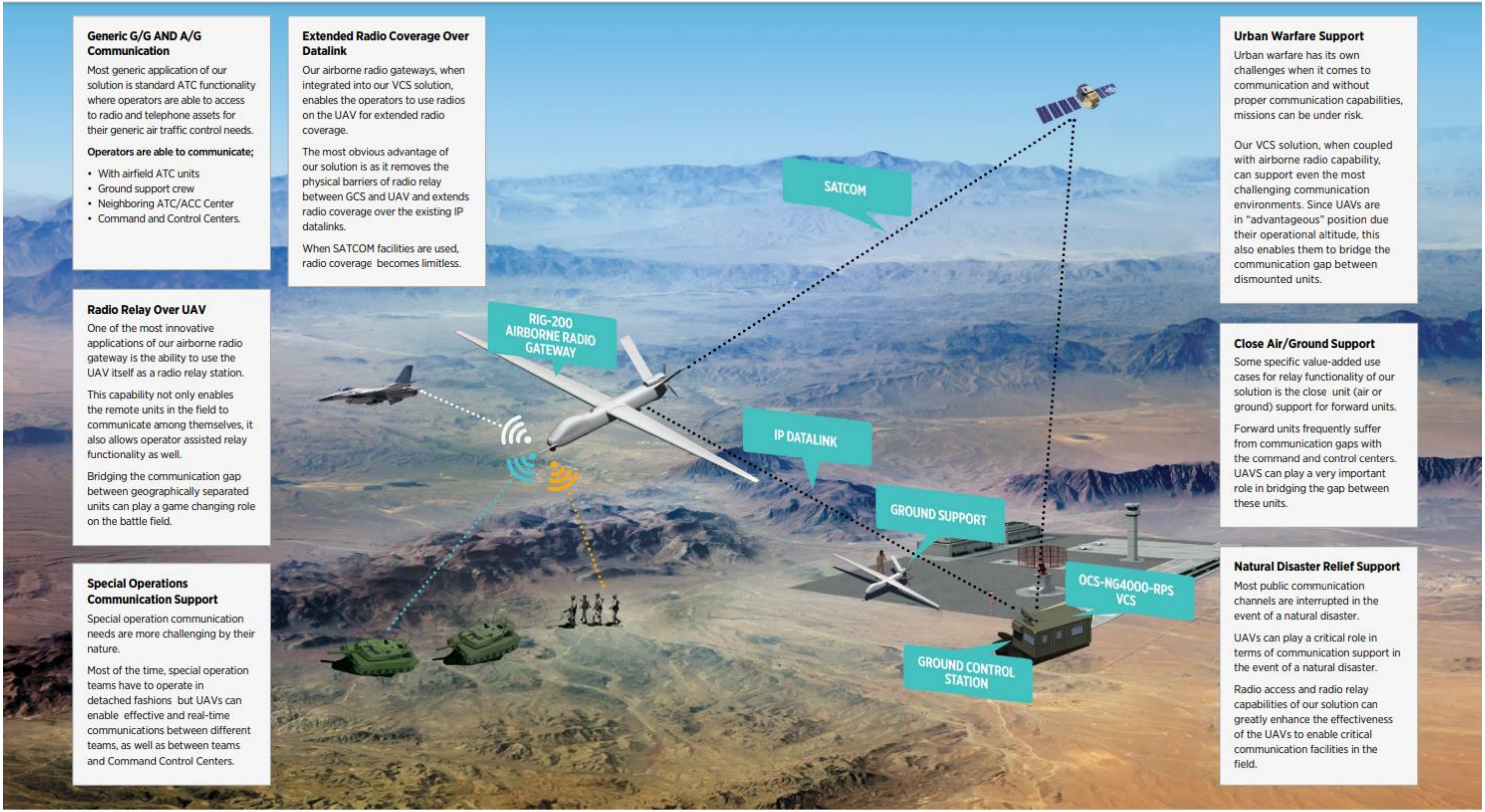
Types of UAVs: Levels of Autonomy & Drone Applications



Level 5 – Full Automation
The drone controls itself under all circumstances with no expectation of human intervention. This includes full-time automation of all flying tasks under any conditions.

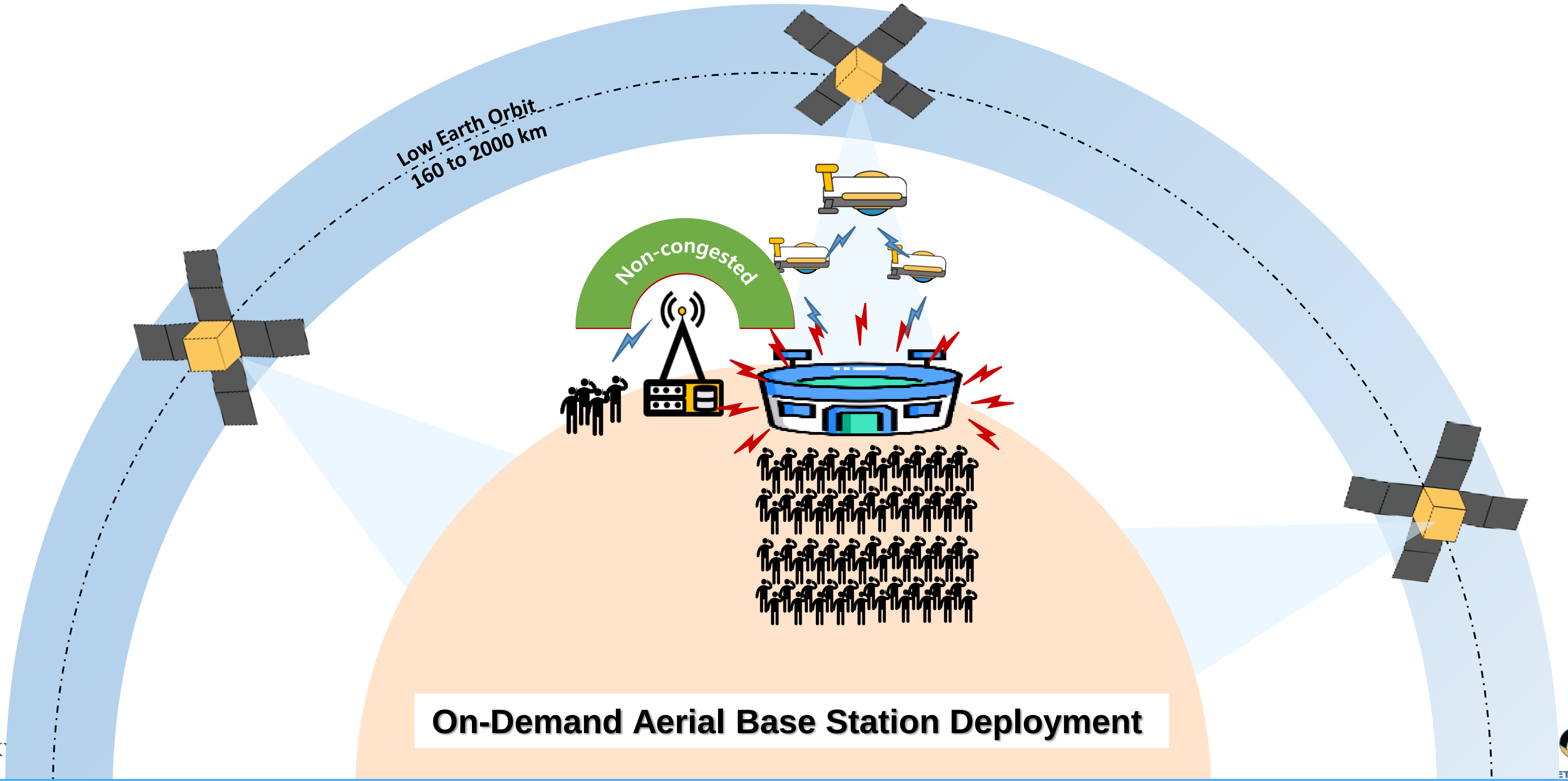
https://dronelife.com/2019/03/11/droneii-tech-talk-unraveling-5-levels-of-drone-autonomy/

Industrial Applications: Military Applications



http://www.uavvoice.com/Catalogue_Communication_System_for_UAV.pdf

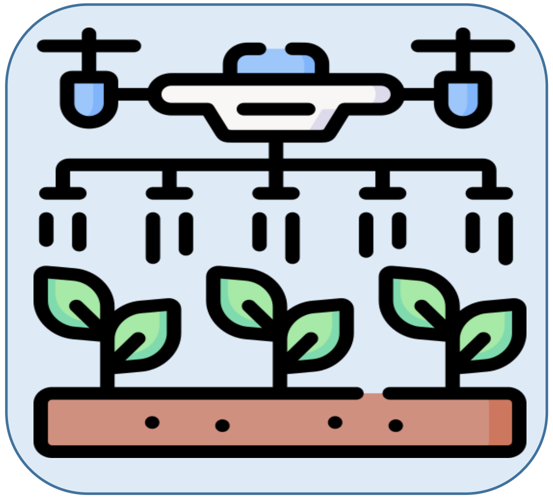
Industrial Applications: Temporary Events



On-Demand Aerial Base Station Deployment

Industrial Applications: Smart Farming

- To access the vegetation health by using Remote Sensing (RS) techniques and image analytics.
- One of the most applied RS techniques is aerial monitoring, by using images captured by satellites, manned aircrafts and UAV
- Satellites images are very expensive for a typical farmer, usually their resolution and quality are not satisfactory and practical due to weather conditions
- Aerial images captured by human-crewed aircrafts present a better quality compared to the satellite images, but this method is also very expensive
- Small UAVs, also known as drones are characterized as a more economical solution

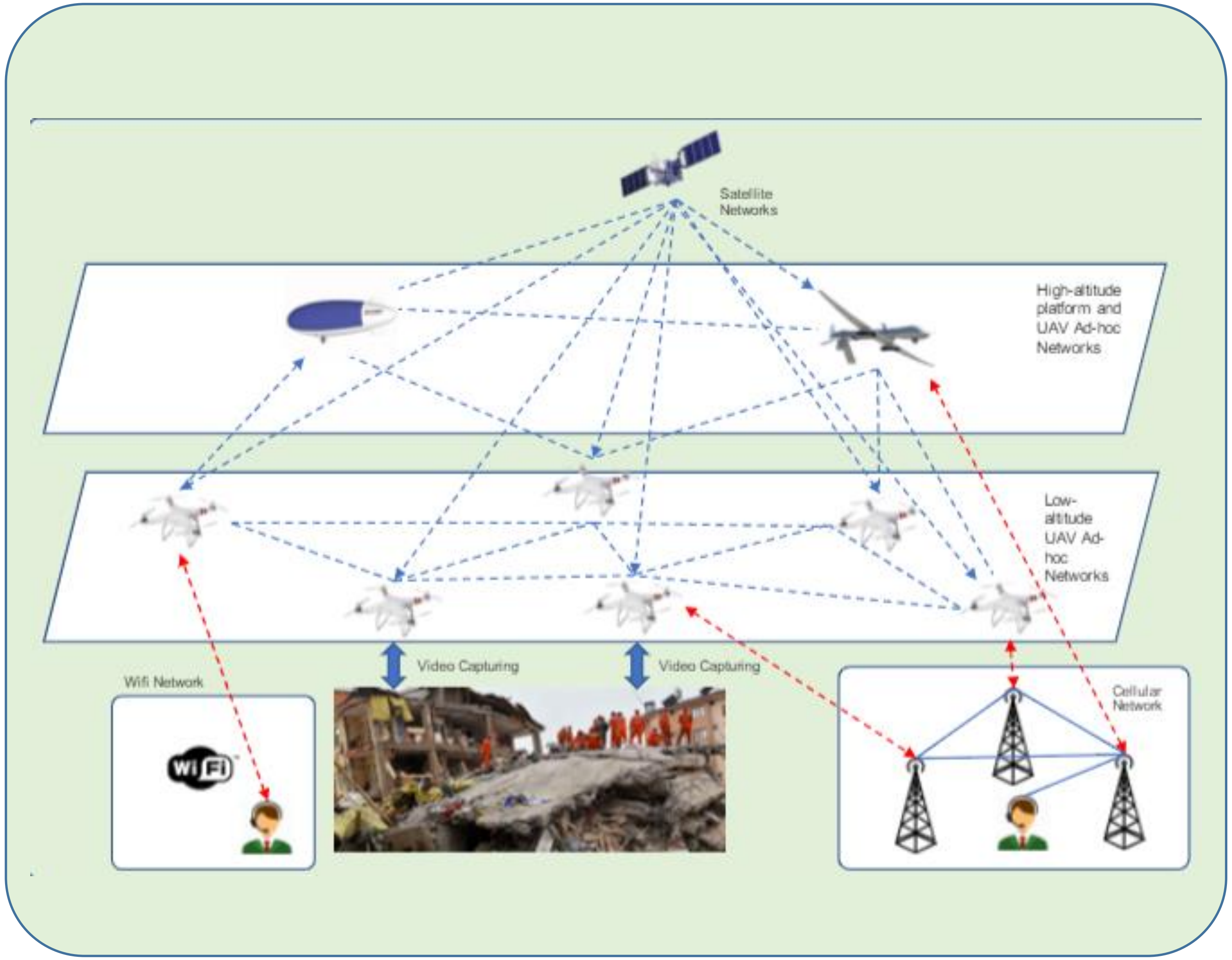


Panagiotis Radoglou-Grammatikis, Panagiotis Sarigiannidis, Thomas Lagka, Ioannis Moscholios, " A compilation of UAV applications for precision agriculture, Computer Networks, 2020.

Industrial Applications: Disaster Areas

- At the top level, UAVs connect to the GPS satellite by quipping receiver on board, which periodically provides the geolocation and time information

- This is critically important for UAVs to accurately and safely accomplish the disaster response tasks



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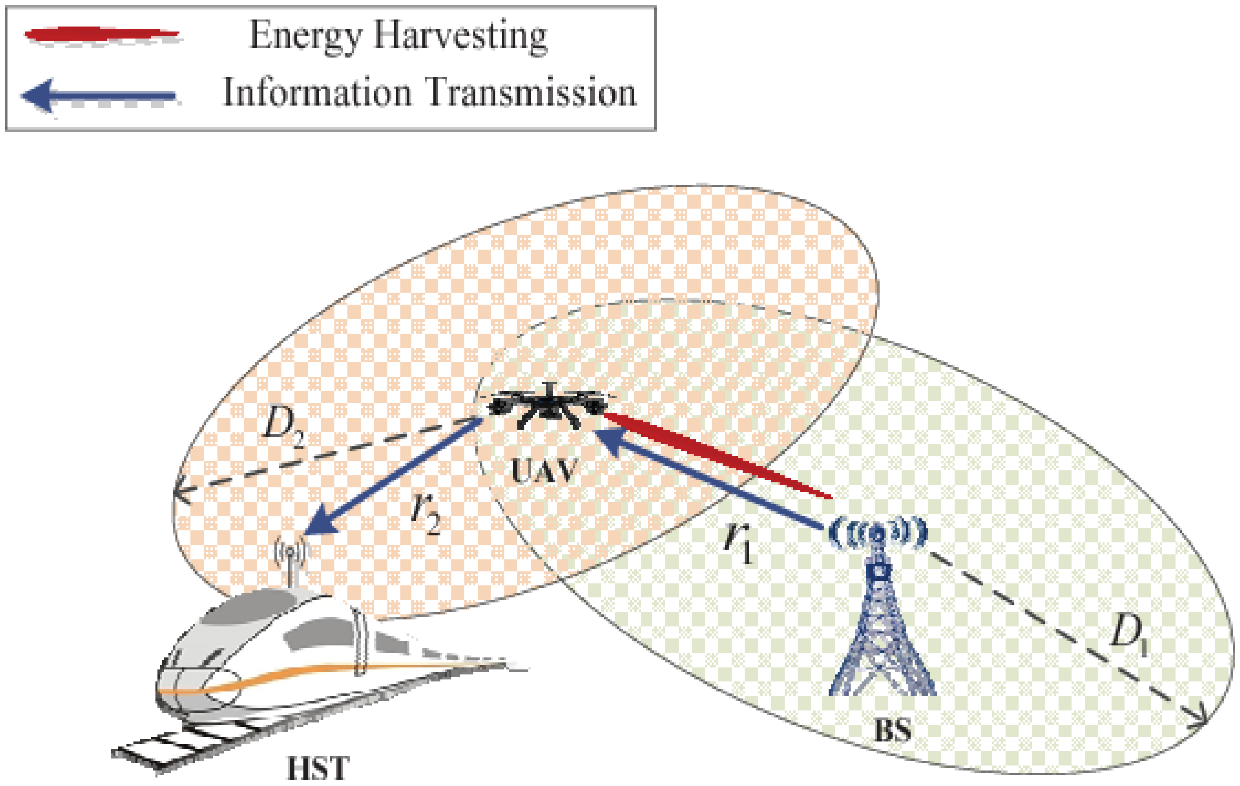
- UAV can also be used as a relay for vehicles and high speed trains



Haitham S. Khallaf, and Murat Uysal, “UAV-Based FSO Communications for High Speed Train Backhauling”, IEEE WCNC 2019.

Challenges to deploy UAVs in Communication System

- UAVs are energy constrained devices. Therefore, efficient energy management is essential.

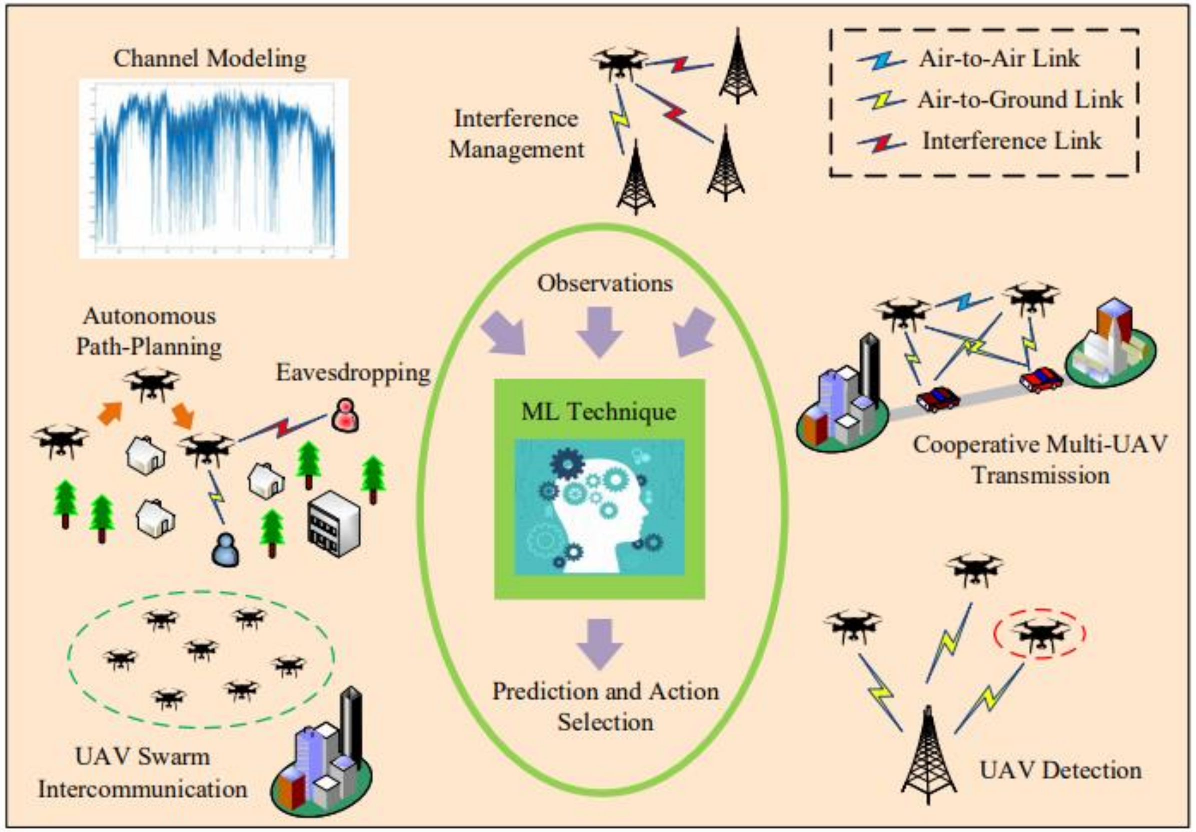
- Optimizing energy-aware trajectory for the good channel quality

- Allocating optimal communication and computation resources to overcome the onboard energy limitation while meeting the users' QoS requirements

- Delploying dynamically a swarm of UAVs in an automatic manner to mitigate interference and avoid collision

Applications of the AI/ML in UAV-based communications

- Interference Management
- Autonomous Path-Planning
- UAV Swarm Intercommunication
- Cooperative Multi-UAV Transmission



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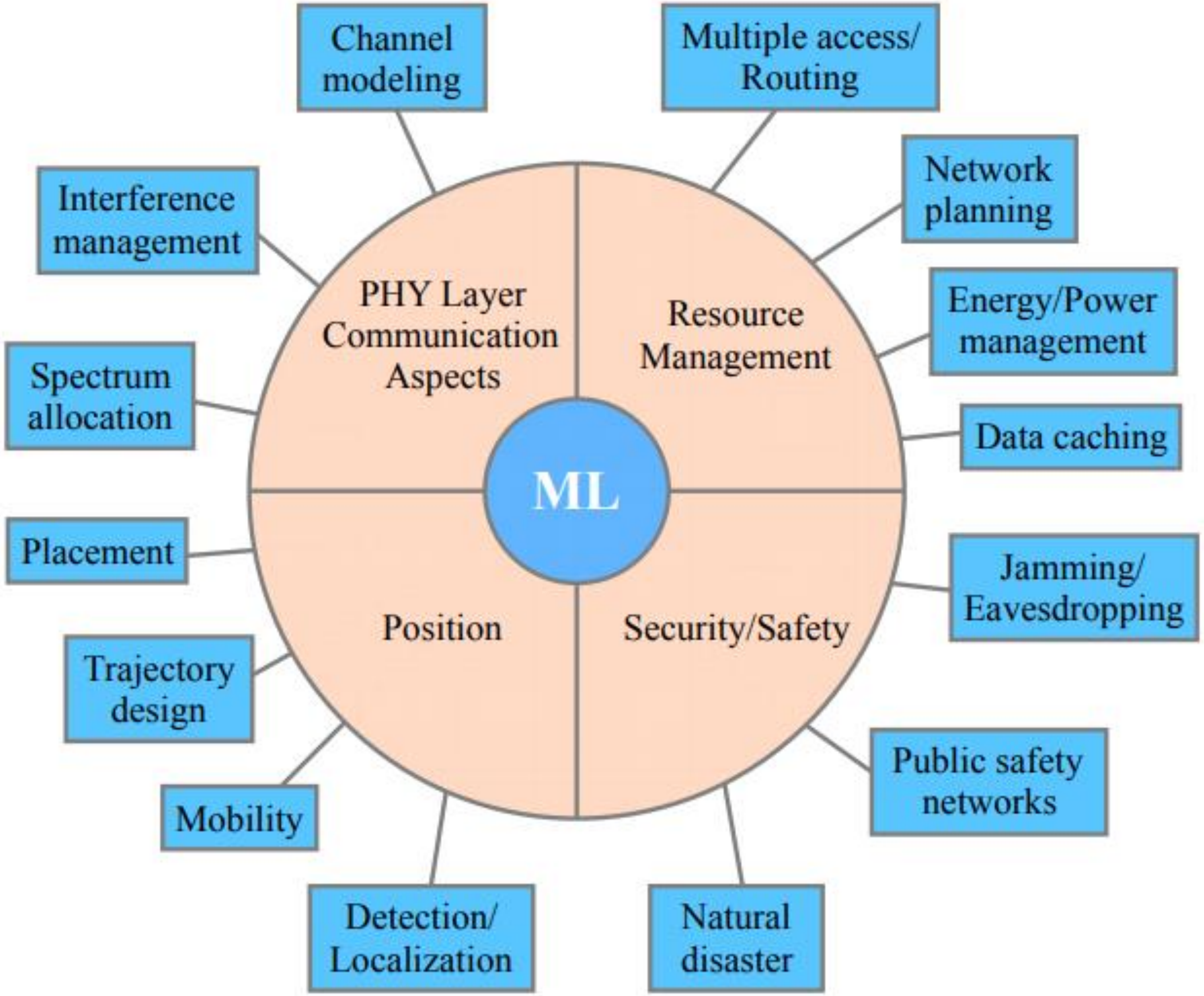
Applications of the AI/ML in UAV-based communications



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Use Case 1: Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks

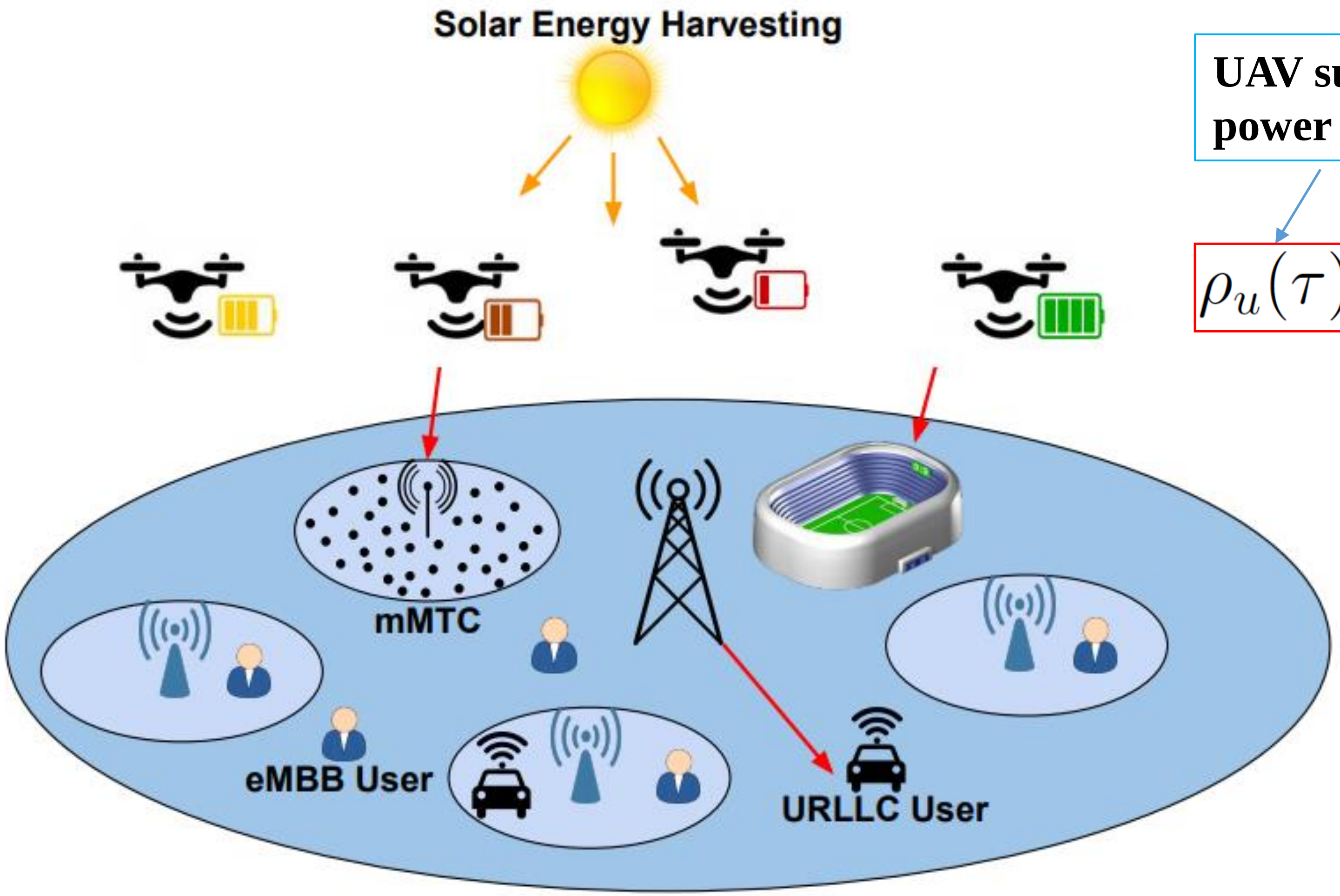
- Introduction
- System Model
- Ruin Theory Preliminaries
- Problem Formulation
- Solution Approach
- Simulation Results

UAV-Assisted Cellular Networks

- Communication features of UAV
  - Line-of-site communication at high altitudes
  - Dynamic placement at desired locations
  - Flexibility and automation

- UAV Communication Challenges
  - Energy efficiency
  - Trajectory design
  - Channel modelling
  - Deployment
  - Interference management
  - Resource allocation

System model of UAV-assisted cellular network



$$\underbrace{\boxed{\rho_u(\tau)}}_{\text{UAV surplus power}} = \underbrace{\boxed{\rho_0}}_{\text{UAV initial power}} + \underbrace{\boxed{\rho\tau}}_{\text{Harvested power}} - \sum_{k\in\mathcal{K}} \underbrace{\boxed{P_{uk}}}_{\text{Transmit power}} - \underbrace{\boxed{\rho_h}}_{\text{Hovering power}}$$

K : number of users

Aunas Manzoor, C. S. Hong et al. "Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks". arXiv preprint arXiv:2006.00815, 2020.

UAV Channel Model

Power

Channel gain

- SINR:

$$\gamma_{jk} = \frac{\boxed{P_{jk}}\boxed{h_{jk}}}{\boxed{\sum_{j'\in\mathcal{J}\setminus\{j\}} P_{j'k}h_{j'k}} + \boxed{\sigma^2}}$$

Interference

Noise

J: UAV-BS
LoS: Line of Sight

Pathloss

- Channel gain:

$$\boxed{h_{jk} = 10^{-\boxed{\delta_{jk}}/10}}$$

Los pathloss

LoS losses

- Path-loss:

$$\boxed{\delta_{uk}^{\mathrm{LoS}}} = 20\log\left(\frac{4\pi d_{uk} f}{c}\right) + \boxed{L_{\mathrm{LoS}}},$$

Non-Los pathloss

Non-Los Losses

$$\boxed{\delta_{uk}^{\mathrm{NLoS}}} = 20\log\left(\frac{4\pi d_{uk} f}{c}\right) + \boxed{L_{\mathrm{NLoS}}},$$

Total pathloss

Probability of non-Los

$$\boxed{\delta_{uk}} = \mathrm{Pr}_{uk}^{\mathrm{LoS}}\delta_{uk}^{\mathrm{LoS}} + \boxed{\mathrm{Pr}_{uk}^{\mathrm{NLoS}}}\delta_{uk}^{\mathrm{NLoS}},$$

Environmental constants

- Probability of LoS:

$$\mathrm{Pr}_{uk}^{\mathrm{LoS}} = \frac{1}{1 + \boxed{a}\exp[\boxed{b}(\frac{180}{\pi}\tan^{-1}\frac{h_u}{d_{uk}}) - a]},$$

d_{uk}:distance between BS j and cellular user k
c: speed of light
f: channel frequency

Association

Bandwidth

SNR

- Data rate:

$$R_{jk} = \boxed{x_{jk}}\boxed{\omega_{jk}}\log(1 + \boxed{\gamma_{jk}})$$

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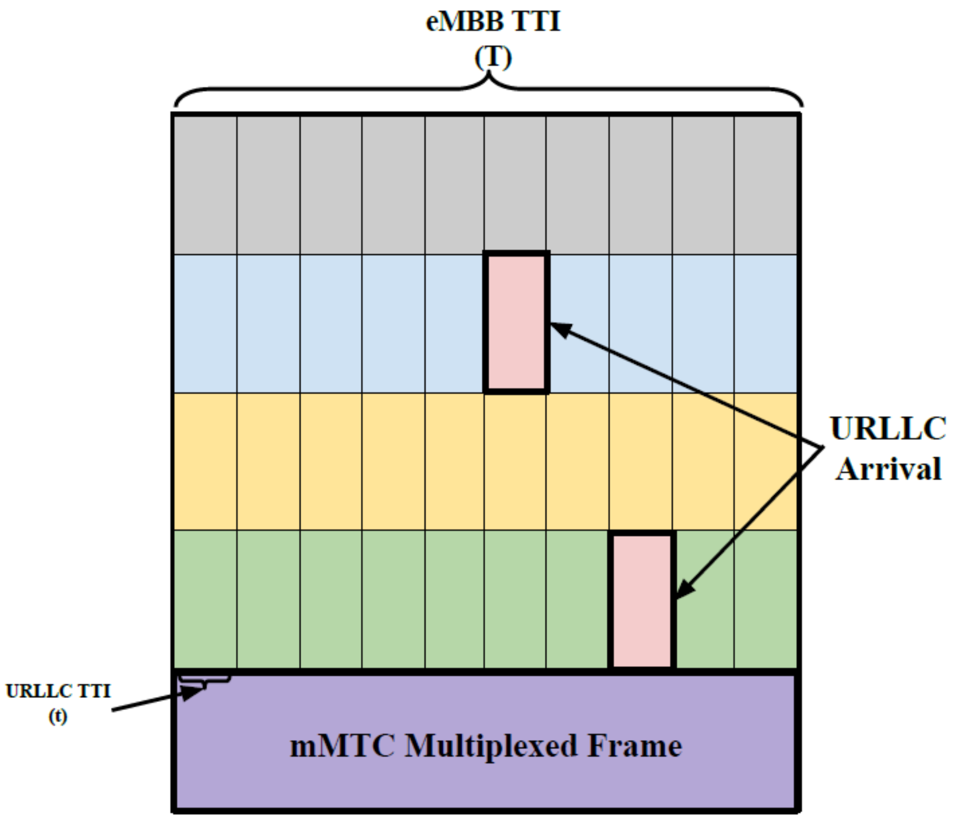
5G-NR coexistence frame structure



URLLC Association

eMBB Rate

The achievable eMBB rate: $$D_{jk}\left(x_{jk}, P_{jk}\right) = \left(T - t \sum_{k' \in \mathcal{K}_u} \boxed{x_{jk'}}\right) \boxed{R_{jk},} \quad \forall k \in \mathcal{K}_e,$$

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Ruin Theory Preliminaries

- Ruin theory expresses an insurer’s vulnerability of bankruptcy
- Surplus process represents the insurer’s capital at a time instant, t, and comprises two opposing cash flows
  - The insurance premiums
  - Random claims

$$\rho_u(\tau) = \overbrace{\boxed{\rho_0}}^{\textbf{Initial power}} + \overbrace{\boxed{\rho\tau}}^{\textbf{Premium (harvesting power)}} - \overbrace{\boxed{S_u}}^{\substack{\textbf{Random claims} \\ \textbf{(power cosumed by transmitting)}}}$$

- Definition of Probability of ruin:

$$\boxed{\psi(\rho_0, \tau) = \Pr[\rho_u(s) < 0, \textit{ for some } s \textit{ as } 0 < s < \tau]}$$

Aunas Manzoor, C. S. Hong et al. “Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks”. arXiv preprint arXiv:2006.00815, 2020.

Total transmission and processing cost minimization problem.

Data rate

Probability of ruin

$$\max_{\boldsymbol{x},\boldsymbol{P}} \quad \varsigma \sum_{j\in\mathcal{J}} \sum_{k\in\mathcal{K}} \boxed{D_{jk}\left(x_{jk}, P_{jk}\right)} - \xi \sum_{u\in\mathcal{U}} \boxed{\psi_u(\rho_0, t)}, \tag{11}$$

$$\sum_{k\in\mathcal{K}} P_{jk} \le \rho_j, \quad \forall j \in \{\{0\} \cup \mathcal{S}\}, \tag{11a}$$

BS transmission power budget

$$\Pr\left(\gamma_{jk'} \ge \zeta\right) \ge (1-\epsilon), \quad \forall j \in \mathcal{J}, \forall k' \in \mathcal{K}_u, \tag{11b}$$

URLLC reliability

$$\sum_{k'\in\mathcal{K}_u} x_{jk'} = \lambda_u, \quad \forall j \in \mathcal{J}, \tag{11c}$$

URLLC latency

Ensuring the immediate scheduling

$$\sum_{j\in\mathcal{J}} x_{jk} = 1, \quad \forall k \in \mathcal{K}, \tag{11d}$$

Unique user association

$$0 \le P_{jk} \le p_{\max}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}, \tag{11e}$$

$$x_{jk} \in \{0,1\}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}. \tag{11f}$$

Variable bounds

Aunas Manzoor, C. S. Hong et al. "Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks". arXiv preprint arXiv:2006.00815, 2020.

URLLC Allocation

- **URLLC Association:** At time slot t, λ_u number of URLLC users are scheduled in the same slot. A user k' is associated with the BS j which delivers best SINR
- **URLLC Power allocation:** Optimal power allocation to meet certain SINR threshold which ensures the URLLC reliability

$$\Pr\left(\gamma_{jk'} \geq \zeta\right) \text{ can be expressed as CDF } F_{\gamma_{jk'}}(\zeta)$$

SINR

SINR Threshold

Reliability

$$\Pr\left(\boxed{\gamma_{jk'}} \geq \boxed{\zeta}\right) \geq \left(\boxed{1-\epsilon}\right) \longrightarrow F_{\gamma_{jk'}}(\zeta) \geq (1-\epsilon) \longrightarrow \zeta \geq \mathcal{F}^{-1}_{\gamma_{jk'}}(1-\epsilon)$$

- Optimal solution lies on boundary $\gamma_{jk'} = \zeta$
- Compute optimal power

$$P^*_{jk'} = \frac{\mathcal{F}^{-1}_{\gamma_{jk'}}(1-\epsilon)(1+I)}{h_{jk}}$$

$$\gamma_{jk} = \frac{P_{jk}h_{jk}}{\sum_{j'\in\mathcal{J}\setminus\{j\}} P_{j'k}h_{j'k} + \sigma^2}$$

$$I = \sum_{j'\in\mathcal{J}\setminus\{j\}} P_{j'k}h_{j'k} + \omega_{jk}\sigma^2$$

eMBB User Association

- Association problem:

$$\max_{\boldsymbol{x}} \quad \varsigma \sum_{j\in\mathcal{J}} \sum_{k\in\mathcal{K}} D'_{jk}\left(x_{jk}, P_{jk}\right) - \xi \sum_{u\in\mathcal{U}} \psi_u(\rho_0, t),$$

$$\sum_{j\in\mathcal{J}} x_{jk} = 1, \quad \forall k \in \mathcal{K},$$

$$x_{jk} \in \{0, 1\}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}.$$

$$\eta_{jk} := \alpha(1 - \psi_u(\rho_0, t))\gamma_{jk}$$

Control factor

the probability of survival

Algorithm 1 User Association Algorithm

```
Input: J, K, P_jk, ρ_j
initialize: x*_jk = 0
Step 1:
Compute ψ_u(ρ_0, t) from (10)
Compute η_jk from (16)
for k = 1 to K do
    Select single BS j with max_{j∈J} η_jk
end for
Step 2:
for j = 1 to J do
    Initialize P = ρ_j
    while P ≥ 0 do
        Find max_{k∈K} γ_jk
        Update x*_jk = 1, and P = P − P_jk
        Remove max_{k∈K} γ_jk from SINR vector γ_jk
    end while
end for
```

eMBB Power Allocation

- Power Allocation Problem:

$$\max_{\boldsymbol{P}} \quad \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}_e} R'_{jk},$$
$$\text{s.t.} \quad \sum_{k \in \mathcal{K}_e} P_{jk} \leq \rho_j - \sum_{k' \in \mathcal{K}_u} P^*_{jk'}, \quad \forall j \in \{\{0\} \cup \mathcal{S}\},$$
$$0 \leq p_{jk} \leq p_{\max}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_e.$$

the optimal power allocation

- Standard Form of Power Allocation Problem:

$$\min_{\boldsymbol{P}} \quad -\sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}_e} x^*_{jk} \omega_{jk} \log\left(1 + \gamma_{jk}\right),$$
$$\text{s.t.} \quad \sum_{k \in \mathcal{K}_e} P_{jk} = \rho_j - \sum_{k' \in \mathcal{K}_u} P^*_{jk'}, \quad \forall j \in \mathcal{J},$$
$$-P_{jk} \leq 0, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_e$$
$$P_{jk} \leq p_{\max}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_e.$$

Aunas Manzoor, C. S. Hong et al. "Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks". arXiv preprint arXiv:2006.00815, 2020.

eMBB Power Allocation

- Lagrangian Function:

$$\mathcal{L}(\boldsymbol{P},\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu}) = -\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}_e} x^*_{jk}\omega_{jk}\log\left(1+\gamma_{jk}\right) + \sum_{j\in\mathcal{J}}\lambda_j\left(\sum_{k\in\mathcal{K}_e} P_{jk} - \rho_j + \sum_{k'\in\mathcal{K}_u} P^*_{jk'}\right) + \sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}_e}\mu_{jk}P_{jk} + \sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}_e}\nu_{jk}(P_{jk}-p_{\max}).$$

$$\theta_{jk} = \frac{h_{jk}}{1+\sum_{j'\in\mathcal{J}\setminus\{0,j\}} P_{j'k}h_{j'k} + \omega_{jk}\sigma^2},$$

Lagrangian multiplier for power budget constraint of BS

- KKT Conditions

$$\nabla\mathcal{L}(\boldsymbol{P}) = -\frac{x^*_{jk}\omega_{jk}\theta_{jk}}{(1+\theta_{jk}P_{jk})} + \lambda_j - \mu_{jk} + \nu_{jk} = 0, \quad \forall j\in\mathcal{J}, k\in\mathcal{K}_e,$$

$$\mu_{jk}P_{jk} = 0, \quad \forall j\in\mathcal{J}, k\in\mathcal{K}_e,$$

$$\boxed{P_{jk} > 0, \implies \mu_{jk} = 0}$$

$$\nu_{jk}(P_{jk}-p_{\max}), \quad \forall j\in\mathcal{J}, k\in\mathcal{K}_e,$$

$$\boxed{(P_{jk}-p_{\max}) > 0, \implies \nu_{jk} = 0}$$

$$\mu_{jk},\nu_{jk} \geq 0, \quad \forall j\in\mathcal{J}, k\in\mathcal{K}_e,$$

- Optimal Power

$$P^*_{jk} = \min\left\{p_{\max}, \left[\frac{x^*_{jk}\omega_{jk}}{\boxed{\lambda_j}} - \frac{1}{\theta_{jk}}\right]^+\right\}, \quad \forall j\in\mathcal{J}, k\in\mathcal{K}_e.$$

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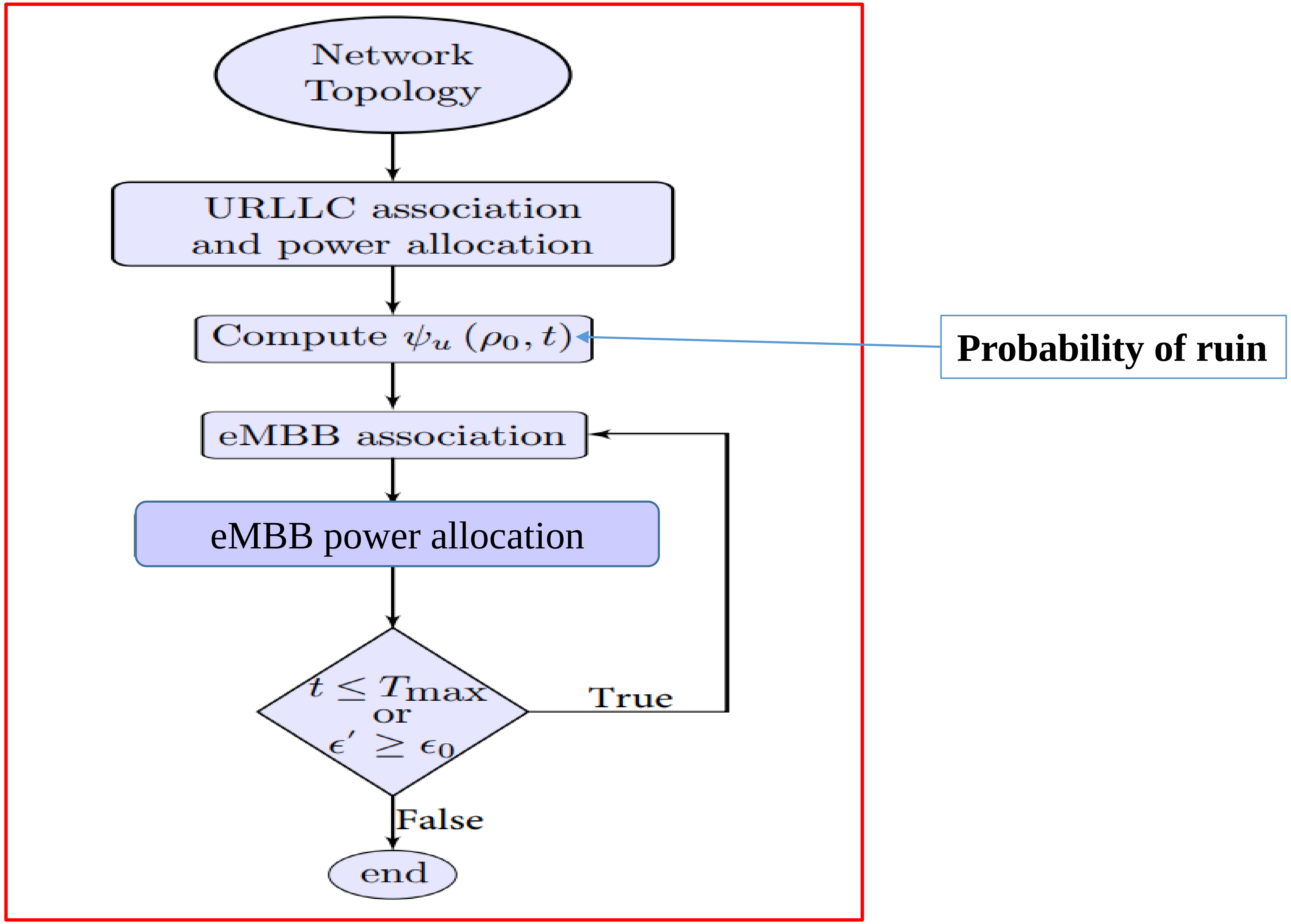
eMBB Power Allocation

$$\nabla \mathcal{L}(\boldsymbol{P}) = -\frac{x^*_{jk}\omega_{jk}}{1 + P_{jk}\boxed{\frac{h_{jk}}{I+\sigma^2}}}\boxed{\frac{h_{jk}}{I+\sigma^2}} + \lambda_j - \mu_{jk}$$
$$+\nu_{jk} = 0, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_e,$$

$$\boxed{\theta_{jk} = \frac{h_{jk}}{I+\sigma^2},}$$

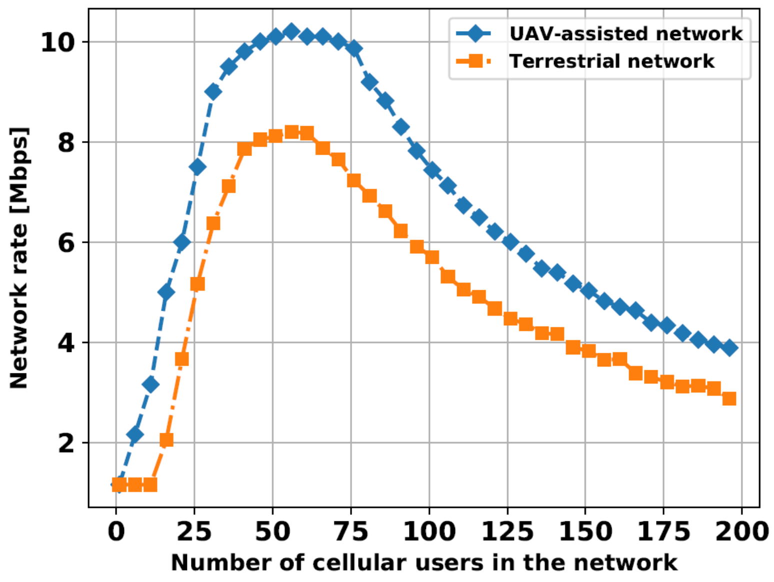
$$\boxed{\begin{aligned}\nabla \mathcal{L}(\boldsymbol{P}) = -\frac{x^*_{jk}\omega_{jk}\theta_{jk}}{(1 + \theta_{jk}P_{jk})} + \lambda_j - \mu_{jk} \\ +\nu_{jk} = 0, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_e,\end{aligned}}$$

Systematic Diagram of Proposed Algorithm

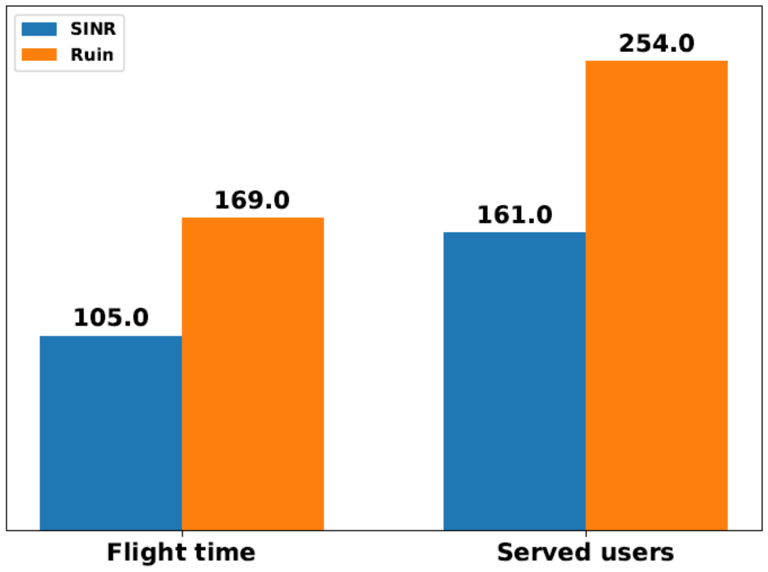


Aunas Manzoor, C. S. Hong et al. "Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks". arXiv preprint arXiv:2006.00815, 2020.

Performance Evaluation (1)



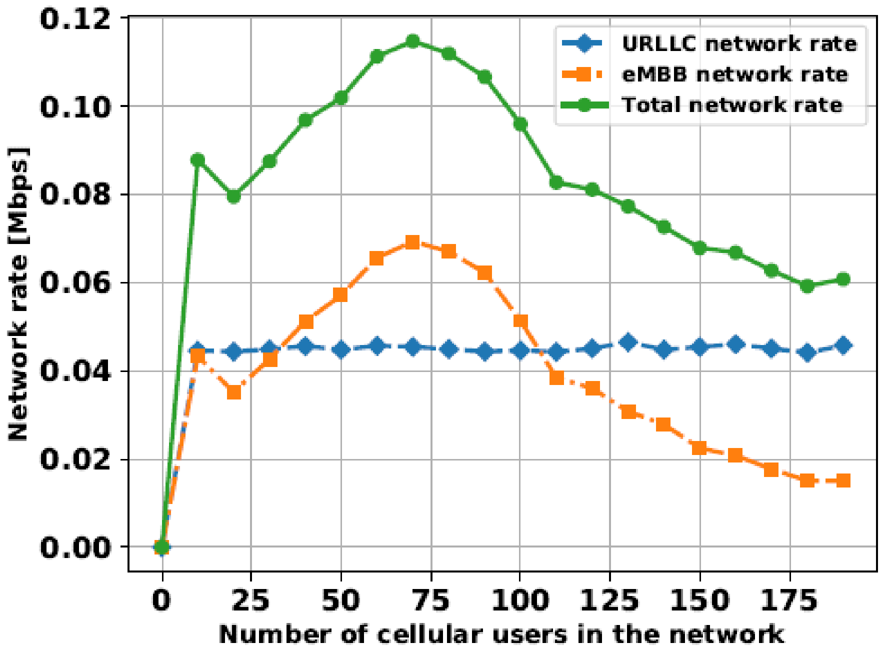
Network rate vs. number of cellular users in the network.



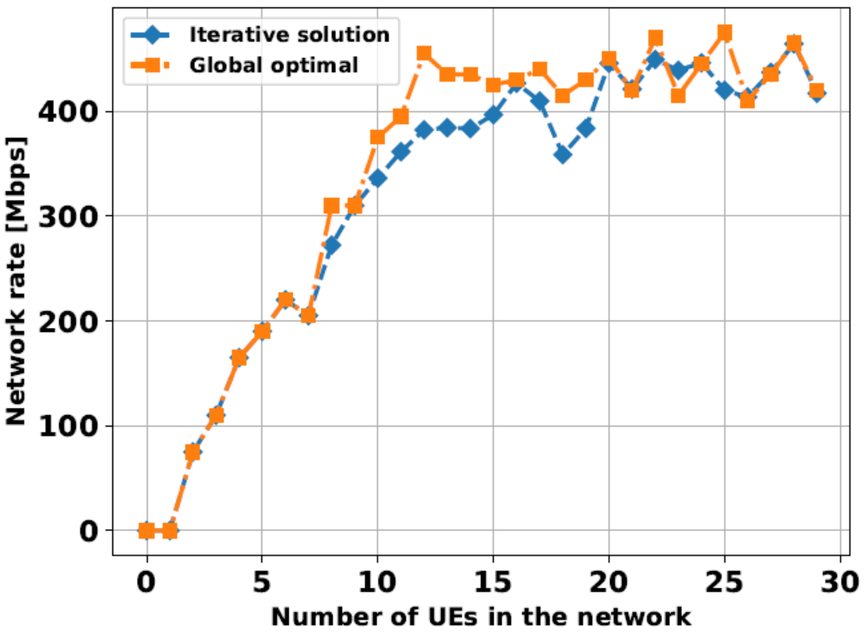
Comparison of ruin and SINR-based approach for UAV flight time and number of served users.

Aunas Manzoor, C. S. Hong et al. "Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks". arXiv preprint arXiv:2006.00815, 2020.

Performance Evaluation (2)



Comparison of ruin and SINR-based approach for UAV flight time and number of served users.



Network rate vs. number of cellular users in the network.

Aunas Manzoor, C. S. Hong et al. "Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks". arXiv preprint arXiv:2006.00815, 2020.

Summary

- The UAV-assisted cellular networks to enhance the cellular network capacity is studied.
- We have formulated a joint optimization problem for the user association and power allocation for the 5G NR traffic classifications.
- First, the probability of ruin is used to estimate the possible number of cellular users to be associated with each UAV.
- Then we have iteratively solved the power allocation problem.
- Simulation results have demonstrated the effectiveness of the proposed ruin-based energy-efficiency scheme.

Use Case 2: Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing

- Introduction
- System Model
- Problem Formulation
- Solution Approach
- Simulation Results

- Recently, unmanned aerial vehicles (UAVs) have been widely deployed to extend the coverage area of the cellular networks and to provide network services to mobile devices where cellular infrastructures are not deployed yet

- Moreover, by implementing a MEC-enabled UAV, a network operator can provide remote and on-demand MEC services to users that are out of infrastructure coverage area

- However, there are several challenges such as energy minimization of both UAV and mobile users, optimal task offloading, resource allocation, and the UAV's trajectory while satisfying the mobile devices' latency requirement

Yan Kyaw Tun, Yu Min Park, Nguyen H.Tran, Walid Saad, Shashi Raj Pandey, and Choong Seon Hong, "Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing", IEEE Communication Letters, Oct 2020.

System Model

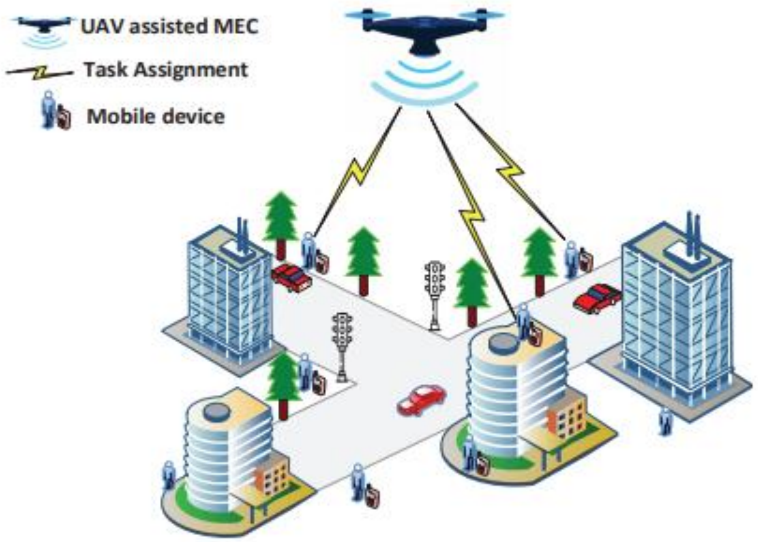


Fig. 1: Illustration of our system model.

- A set of mobile devices : $\mathcal{U}$
- Location of device 'u' : $\boldsymbol{o}_u = [x_u, y_u]^T$
- UAV's total flight period : T
- UAV is flying at fixed altitude : H
- Location of UAV at time 't' : $\mathbf{c}(t) = [x(t), y(t), H]^T, 0 \leq t \leq T$
- Discretize UAV flight period into N time slots
- UAV needs to return initial location at the end of flight period : $\mathbf{c}(1) = \mathbf{c}(N)$

Yan Kyaw Tun, Yu Min Park, Nguyen H.Tran, Walid Saad, Shashi Raj Pandey, and Choong Seon Hong, "Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing", IEEE Communication Letters, Oct 2020.

Communication Model

- Speed constraint of UAV at time slot 'n' :

$$\boxed{\frac{||\boldsymbol{c}(n+1)-\boldsymbol{c}(n)||}{L} \leq V, \forall n \in \mathcal{N}.}$$

LV : the maximum distance that UAV can be traveled by the UAV in each slot

L: Duration

- The energy consumption of UAV flight at time slot 'n':

$$\boxed{E^{\text{fly}}(n) = k\left(\frac{||\boldsymbol{c}(n+1)-\boldsymbol{c}(n))||}{L}\right), \forall n \in \mathcal{N},}$$

$$\boxed{k = 0.5M}$$

UAV weight

- The distance between UAV and device 'u' at time slot 'n':

$$\boxed{d_u(n) = \sqrt{H^2 + ||\boldsymbol{c}(n) - \boldsymbol{o}_u||^2}, \quad \forall u \in \mathcal{U}, \forall n \in \mathcal{N}.}$$

- The achievable data rate of device 'u' at time slot 'n':

$$R_u(n) = \boxed{\alpha_u(n) B \log_2\left(1 + \frac{p_u(n)|h_u(n)|^2}{\sigma^2}\right), \forall u, \forall n,}$$

Association | Bandwidth | Transmit power of device | Channel gain

Local Computing Model

- Computation task of device ‘u’ at time slot ‘n’ can be denoted as tuple:

$$\{\beta_u, a_u(n), T_u(n)\},$$

Required CPU cycles to compute 1-bit of input data

Input data size

Tolerable amount of time to complete task

- Fraction of task executed remotely at UAV and device ‘u’: $l_u(n)$ and $(a_u(n) - l_u(n))$

- Local Computation Latency/delay of device ‘u’:

$$t_u^l(n) = \frac{\beta_u(a_u(n) - l_u(n))}{f_u^l}, \quad \forall u \in \mathcal{U}, \forall n \in \mathcal{N},$$

Computation capacity (cycles/s) of device ‘u’

- Local energy consumption of device ‘u’ at time slot ‘n’:

$$E_u^l(n) = w(f_u^l)^2 \beta_u(a_u(n) - l_u(n)), \quad \forall u \in \mathcal{U}, \forall n \in \mathcal{N},$$

$$w = 5 \times 10^{-27}$$

UAV-Aided Edge Computing Model

- Uplink transmission time of device 'u' when assigning fraction of task $l_u(n)$ to UAV as time slot 'n':

$$\boxed{t_u^{\mathrm{up}}(n) = \frac{l_u(n)}{R_u(n)}, \quad \forall u \in \mathcal{U}, \forall n \in \mathcal{N}.}$$

- The uplink energy consumption:

$$\boxed{E_u^{\mathrm{up}}(n) = \frac{p_u(n) l_u(n)}{R_u(n)}, \quad \forall u \in \mathcal{U}, \forall n \in \mathcal{N}.}$$

- The computation latency at UAV:

$$\boxed{t_u^{\mathrm{comp}}(n) = \frac{\beta_u l_u(n)}{f_u^C(n)}, \quad \forall u \in \mathcal{U}, \forall n \in \mathcal{N},}$$

Computation capacity of UAV allocated to device 'n'

- The energy consumed by the UAV for executing the fraction of task of device 'u':

$$\boxed{E_u^{\mathrm{exe}}(n) = q(f_u^C)^2 \beta_u l_u(n), \quad \forall n \in \mathcal{N},} \qquad \boxed{q = 5 \times 10^{-27}}$$

Yan Kyaw Tun, Yu Min Park, Nguyen H.Tran, Walid Saad, Shashi Raj Pandey, and Choong Seon Hong, "Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing", IEEE Communication Letters, Oct 2020.

Problem Formulation

- To the best of our knowledge, our work is the first to consider the energy minimization of both UAV and mobile devices by jointly optimizing the UAV's trajectory, communication and computation resource allocation, and task assignment. We can formally post this problem as follows:

$$\min_{\boldsymbol{c},\boldsymbol{l},\boldsymbol{\alpha},\boldsymbol{p},\boldsymbol{f}} \left(\sum_{n=1}^{N} \sum_{u=1}^{U} E_u^{l}(n) + E_u^{\mathrm{up}}(n) \right) + \sum_{n=1}^{N} E^{\mathrm{fly}}(n) + \sum_{n=1}^{N} \sum_{u=1}^{U} E_u^{\mathrm{exe}}(n) \quad (15)$$

$$\text{s.t. } t_u^{\mathrm{up}}(n) + t_u^{\mathrm{comp}}(n) \le T_u(n), \quad \forall u \in \mathcal{U}, \forall n \in \mathcal{N}, \quad (15a)$$

$$t_u^{l}(n) \le T_u(n), \forall u \in \mathcal{U}, \forall n \in \mathcal{N}, \quad (15b)$$

Latency constraint of task of each device at each time slot

$$l_u(n) \le a_u(n), \forall u \in \mathcal{U}, \forall n \in \mathcal{N}, \quad (15c)$$

Data size constraint of task of each device

$$\sum_{u=1}^{U} f_u^{C}(n) \le f^{C}(n), \forall n \in \mathcal{N}, \quad (15d)$$

Computation capacity constraint of UAV

$$0 \le p_u(n) \le p_u^{\max}(n), \forall n \in \mathcal{N}, \forall u \in \mathcal{U}, \quad (15e)$$

Power constraint of each device

$$\sum_{u=1}^{U} \alpha_u(n) \le 1, 0 \le \alpha_u(n) \le 1, \forall u \in \mathcal{U}, \forall n \in \mathcal{N}, \quad (15f)$$

Fraction of bandwidth allocated to each device

$$\frac{||\mathbf{c}(n+1) - \mathbf{c}(n)||}{L} \le V, \forall n \in \mathcal{N}, \quad (15g)$$

Speed constraint of UAV

$$\boldsymbol{c}(1) = \boldsymbol{c}(N), \quad (15h)$$

Location of UAV at initial and final flight

Yan Kyaw Tun, Yu Min Park, Nguyen H.Tran, Walid Saad, Shashi Raj Pandey, and Choong Seon Hong, "Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing", IEEE Communication Letters, Oct 2020.

- Our proposed problem is MINLP(mixed integer nonlinear programming). Therefore, it is an NP-hard problem. Therefore, we use Block Successive Upper-bound Minimization (BSUM) method to solve the problem. Then, we rewrite the above mentioned problem as follow:

$$\min_{\substack{\boldsymbol{c}\in\mathcal{C},\boldsymbol{l}\in\mathcal{L},\boldsymbol{\alpha}\in\alpha,\\ \boldsymbol{p}\in\mathcal{P},\boldsymbol{f}\in\mathcal{F}}} \quad \mathcal{O}(\boldsymbol{c},\boldsymbol{l},\boldsymbol{\alpha},\boldsymbol{p},\boldsymbol{f})$$

where $\mathcal{O}(\boldsymbol{c},\boldsymbol{l},\boldsymbol{\alpha},\boldsymbol{p},\boldsymbol{f}) = \left(\sum_{n=1}^{N}\sum_{u=1}^{U} E_u^l(n) + E_u^{\mathrm{up}}(n)\right) + \sum_{n=1}^{N} E^{\mathrm{fly}}(n) + \sum_{n=1}^{N}\sum_{u=1}^{U} E_u^{\mathrm{exe}}(n)$. Furthermore,

$$\mathcal{C} \triangleq \{\boldsymbol{c} : t_u^{\mathrm{up}}(n) + t_u^{\mathrm{comp}}(n) \le T_u(n), \frac{||\mathbf{c}(n+1) - \mathbf{c}(n)||}{L} \le V, \forall u \in \mathcal{U}, \forall n \in \mathcal{N}\},$$

$$\mathcal{L} \triangleq \{\boldsymbol{l} : t_u^{\mathrm{up}}(n) + t_u^{\mathrm{comp}}(n) \le T_u(n), t_u^l(n) \le T_u(n), l_u(n) \le a_u(n), \forall u \in \mathcal{U}, \forall n \in \mathcal{N}\},$$

$$\alpha \triangleq \{\boldsymbol{\alpha} : t_u^{\mathrm{up}}(n) + t_u^{\mathrm{comp}}(n) \le T_u(n), \sum_{u=1} \alpha_u(n) \le 1, 0 \le \alpha_u(n) \le 1, \forall u \in \mathcal{U}, \forall n \in \mathcal{N}\},$$

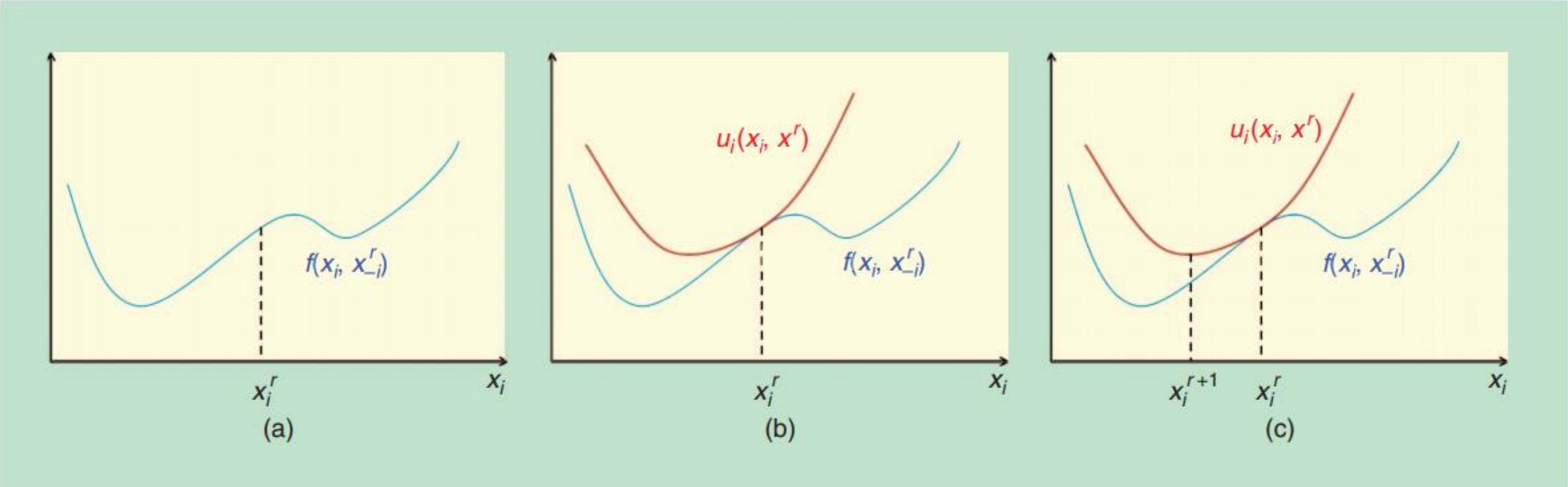
$$\mathcal{P} \triangleq \{\boldsymbol{p} : t_u^{\mathrm{up}}(n) + t_u^{\mathrm{comp}}(n) \le T_u(n), 0 \le p_u(n) \le p_u^{\max}(n), \forall n, \forall u \in \mathcal{U}\},$$

$$\mathcal{F} \triangleq \{\boldsymbol{f} : t_u^{\mathrm{up}}(n) + t_u^{\mathrm{comp}}(n) \le T_u(n), \sum_{u=1}^{U} f_u^C(n) \le f^C(n), \forall u, \forall n \in \mathcal{N}\},$$

- The proximal upper-bound function:

$$\mathcal{O}_i(\boldsymbol{c}_i;\boldsymbol{c}^k,\boldsymbol{l}^k,\boldsymbol{\alpha}^k,\boldsymbol{p}^k,\boldsymbol{f}^k) = \mathcal{O}(\boldsymbol{c}_i;\tilde{\boldsymbol{c}},\tilde{\boldsymbol{l}},\tilde{\boldsymbol{\alpha}},\tilde{\boldsymbol{p}},\tilde{\boldsymbol{f}}) + \frac{\mu_i}{2} \underbrace{\| (\boldsymbol{c}_i - \tilde{\boldsymbol{c}}) \|^2}_{\text{Penalty term}},$$

Yan Kyaw Tun, Yu Min Park, Nguyen H.Tran, Walid Saad, Shashi Raj Pandey, and Choong Seon Hong, "Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing", IEEE Communication Letters, Oct 2020.



[FIG3] The upper-bound minimization step of the BSUM method is shown. Here we assume that coordinate i is updated at iteration $r + 1$. It is clear from the figure that after solving the BSUM subproblem (3), $f(x_i^{r+1}, x_{-i}^r) < f(x_i^r, x_{-i}^r)$, that is, the objective function is strictly decreased.

$$\begin{cases} x_i^r \in \operatorname{argmin}_{x_i \in \mathcal{X}_i} u_i(x_i, x^{r-1}), \forall\, i \in \mathcal{I}^r \\ x_k^r = x_k^{r-1}, \forall\, k \notin \mathcal{I}^r \end{cases}. \qquad (3)$$

Hong, Mingyi, et al. "A unified algorithmic framework for block-structured optimization involving big data: With applications in machine learning and signal processing." *IEEE Signal Processing Magazine* 33.1 (2015): 57-77.

- The solution at each iteration can be updated by solving the following sub-problems:

$$\boldsymbol{c}_i^{(k+1)} \in \min_{\boldsymbol{c}_i \in \mathcal{C}} \mathcal{O}_i\left(\boldsymbol{c}_i; \boldsymbol{c}^{(k)}, \boldsymbol{l}^{(k)}, \boldsymbol{\alpha}^{(k)}, \boldsymbol{p}^{(k)}, \boldsymbol{f}^{(k)}\right), \tag{18}$$

$$\boldsymbol{l}_i^{(k+1)} \in \min_{\boldsymbol{l}_i \in \mathcal{L}} \mathcal{O}_i\left(\boldsymbol{l}_i; \boldsymbol{l}^{(k)}, \boldsymbol{c}^{(k+1)}, \boldsymbol{\alpha}^{(k)}, \boldsymbol{p}^{(k)}, \boldsymbol{f}^{(k)}\right), \tag{19}$$

$$\boldsymbol{\alpha}_i^{(k+1)} \in \min_{\boldsymbol{\alpha}_i \in \boldsymbol{\alpha}} \mathcal{O}_i\left(\boldsymbol{\alpha}_i; \boldsymbol{\alpha}^{k}, \boldsymbol{c}^{(k+1)}, \boldsymbol{l}^{(k+1)}, \boldsymbol{p}^{(k)}, \boldsymbol{f}^{(k)}\right), \tag{20}$$

$$\boldsymbol{p}_i^{(k+1)} \in \min_{\boldsymbol{p}_i \in \mathcal{P}} \mathcal{O}_i\left(\boldsymbol{p}_i; \boldsymbol{p}^{(k)}, \boldsymbol{c}^{(k+1)}, \boldsymbol{l}^{(k+1)}, \boldsymbol{\alpha}^{(k+1)}, \boldsymbol{f}^{(k)}\right), \tag{21}$$

$$\boldsymbol{f}_i^{(k+1)} \in \min_{\boldsymbol{f}_i \in \mathcal{F}} \mathcal{O}_i\left(\boldsymbol{f}_i; \boldsymbol{f}^{(k)}, \boldsymbol{c}^{(k+1)}, \boldsymbol{l}^{(k+1)}, \boldsymbol{\alpha}^{(k+1)}, \boldsymbol{p}^{(k+1)}\right) \tag{22}$$

Algorithm 1 BSUM Algorithm for an Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing

Initialization: Set $k = 0$, $\epsilon_1 > 0$, and find initial feasible solutions $(\boldsymbol{c}^{(0)}, \boldsymbol{l}^{(0)}, \boldsymbol{\alpha}^{(0)}, \boldsymbol{p}^{(0)}, \boldsymbol{f}^{(0)})$;
repeat
  Choose index set $\mathcal{I}^k$;
  Let $\boldsymbol{c}_i^{(k+1)} \in \min_{\boldsymbol{c}_i \in \mathcal{C}} \mathcal{O}_i(\boldsymbol{c}_i; \boldsymbol{c}^{(k)}, \boldsymbol{l}^{(k)}, \boldsymbol{\alpha}^{(k)}, \boldsymbol{p}^{(k)}, \boldsymbol{f}^{(k)})$;
  Set $\boldsymbol{c}_j^{(k+1)} = \boldsymbol{c}_j^k, \forall j \notin \mathcal{I}^k$;
  Find $\boldsymbol{l}_i^{(k+1)}$, $\boldsymbol{\alpha}_i^{(k+1)}$, $\boldsymbol{p}_i^{(k+1)}$, and $\boldsymbol{f}_i^{(k+1)}$ by solving (19), (20), (21), and (22);
  $k = k + 1$;
until $\| \frac{\mathcal{O}_i^{(k)} - \mathcal{O}_i^{(k+1)}}{\mathcal{O}_i^{(k)}} \| \leq \epsilon_1$
Then, set $(\boldsymbol{c}_i^{(k+1)}, \boldsymbol{l}_i^{(k+1)}, \boldsymbol{\alpha}_i^{(k+1)}, \boldsymbol{p}_i^{(k+1)}, \boldsymbol{f}_i^{(k+1)})$ as the desired solution.

Yan Kyaw Tun, Yu Min Park, Nguyen H.Tran, Walid Saad, Shashi Raj Pandey, and Choong Seon Hong, "Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing", IEEE Communication Letters, Oct 2020.

Simulation Results

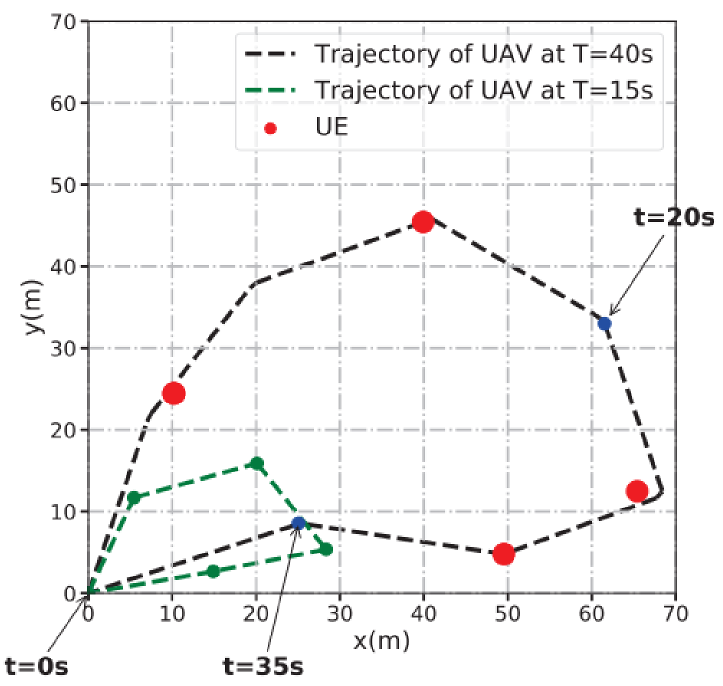
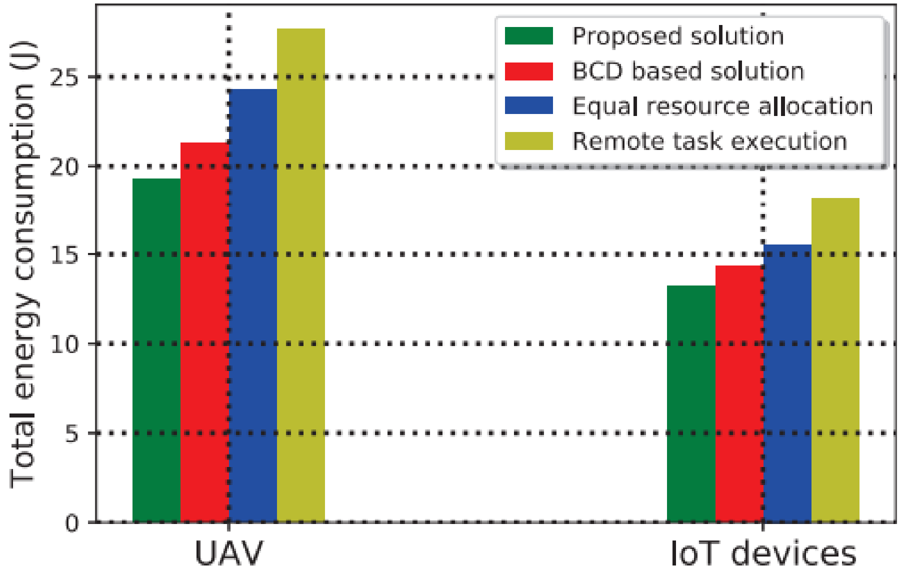


Fig. 2: Trajectories of UAV under different flight period T.

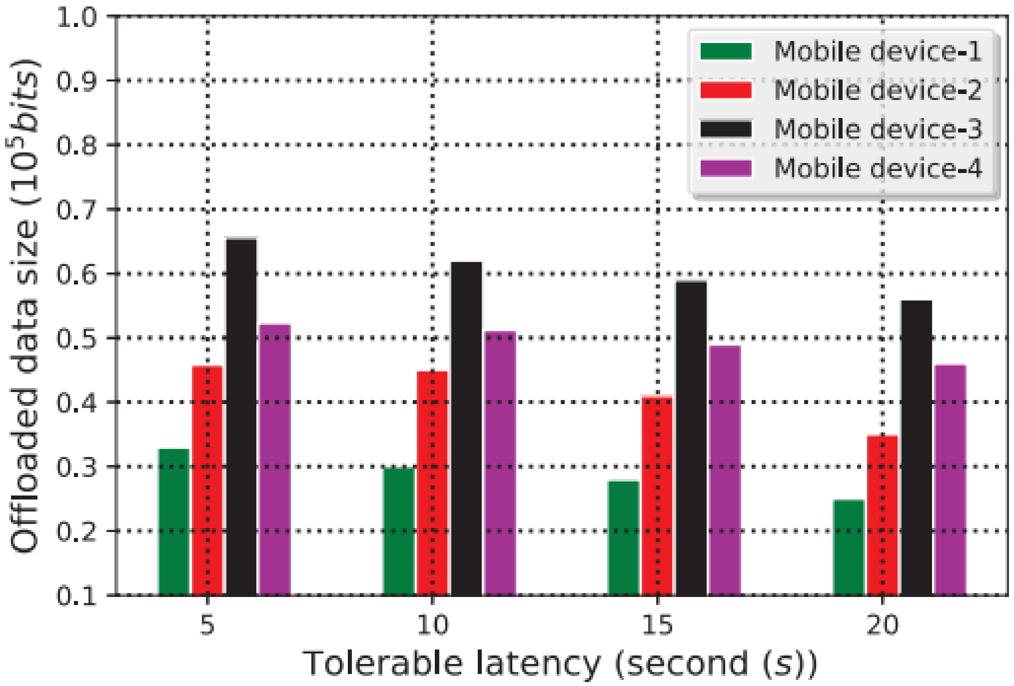


(a)

*BCD: Block Coordinate Descent

3(a) shows energy consumption of UAV and IoT devices.

Yan Kyaw Tun, Yu Min Park, Nguyen H.Tran, Walid Saad, Shashi Raj Pandey, and Choong Seon Hong, "Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing", IEEE Communication Letters, Oct 2020.



(c)

3(c) shows offloaded data size of the task under different tolerable latency.

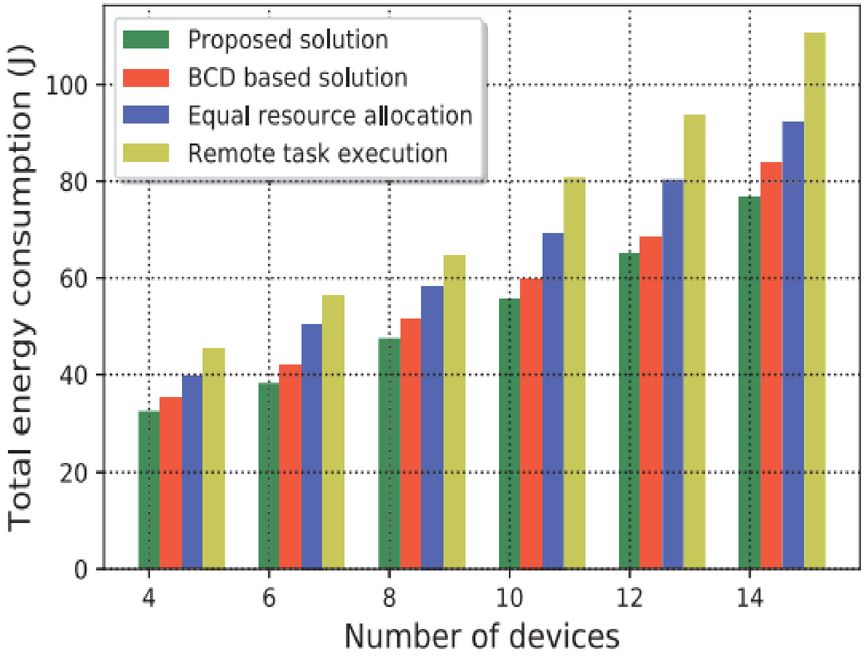


Fig. 4: Energy consumption under different number of mobile devices.

Summary

- In this work, we have studied the problem of energy-efficient UAV trajectory optimization, resource allocation, and task offloading in the UAV-assisted mobile edge computing system.

- We have shown that the proposed problem exhibit a non-convex structure, and thus, it is challenging to solve by using traditional convex optimization techniques.

- To address this issue, we have introduced the BSUM algorithm, which is a powerful tool for non-convex.

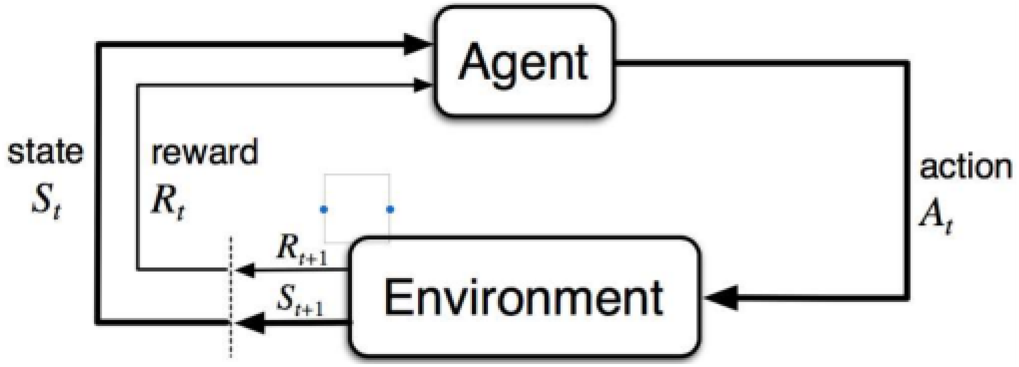
- Finally, we presented the numerical results to show the efficiency of the proposed solution approach where it was clear that our proposed algorithm outperforms other baseline algorithms.

Yan Kyaw Tun, Yu Min Park, Nguyen H.Tran, Walid Saad, Shashi Raj Pandey, and Choong Seon Hong, "Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing", IEEE Communication Letters, Oct 2020.

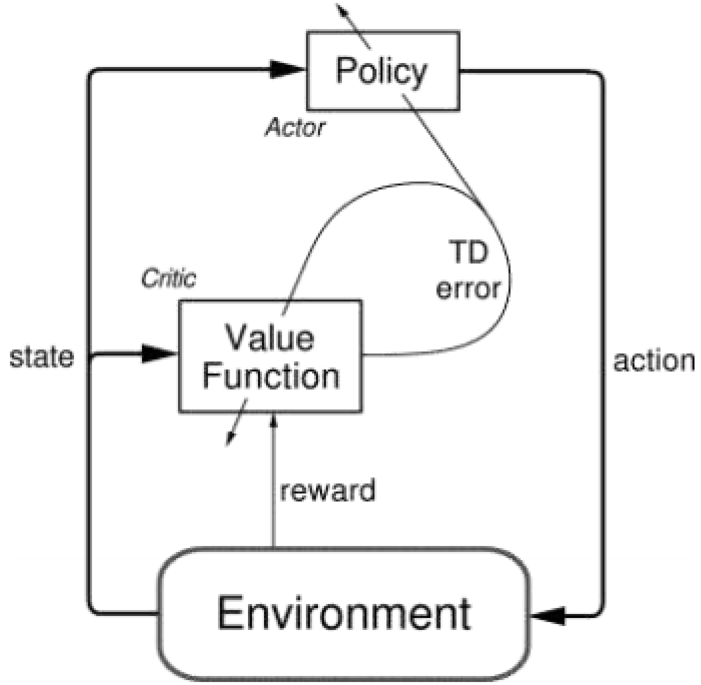
What is Missing till now?

Yes, It is "AI"

- Reinforcement Learning (i.e., Q-Learning)



- Deep Learning
  - Artificial Neural Networks (ANN)
  - Deep Reinforcement Learning (DRL)
    (i.e., Deep Q-Learning)
  - Actor-Critic Learning



Use Case 3: Data Freshness and Energy-Efficient UAV Navigation Optimization: A Deep Reinforcement Learning Approach

- Introduction
- System Model
- Problem Formulation
- Solution Approach
- Simulation Results

- In this work, we design a navigation policy for multiple UAVs where mobile base stations (BSs) are deployed to improve the data freshness and connectivity to the IoT devices.

- We formulate an energy-efficient trajectory optimization problem in which the objective is to maximize the energy efficiency by optimizing the UAV-BS trajectory policy

- We also incorporate different contextual information such as energy and age of information (AoI) constraints to ensures the data freshness at the ground BS.

- Second, we propose an agile deep reinforcement learning with experience replay model to solve the formulated problem concerning the contextual constraints for the UAV-BS navigation.

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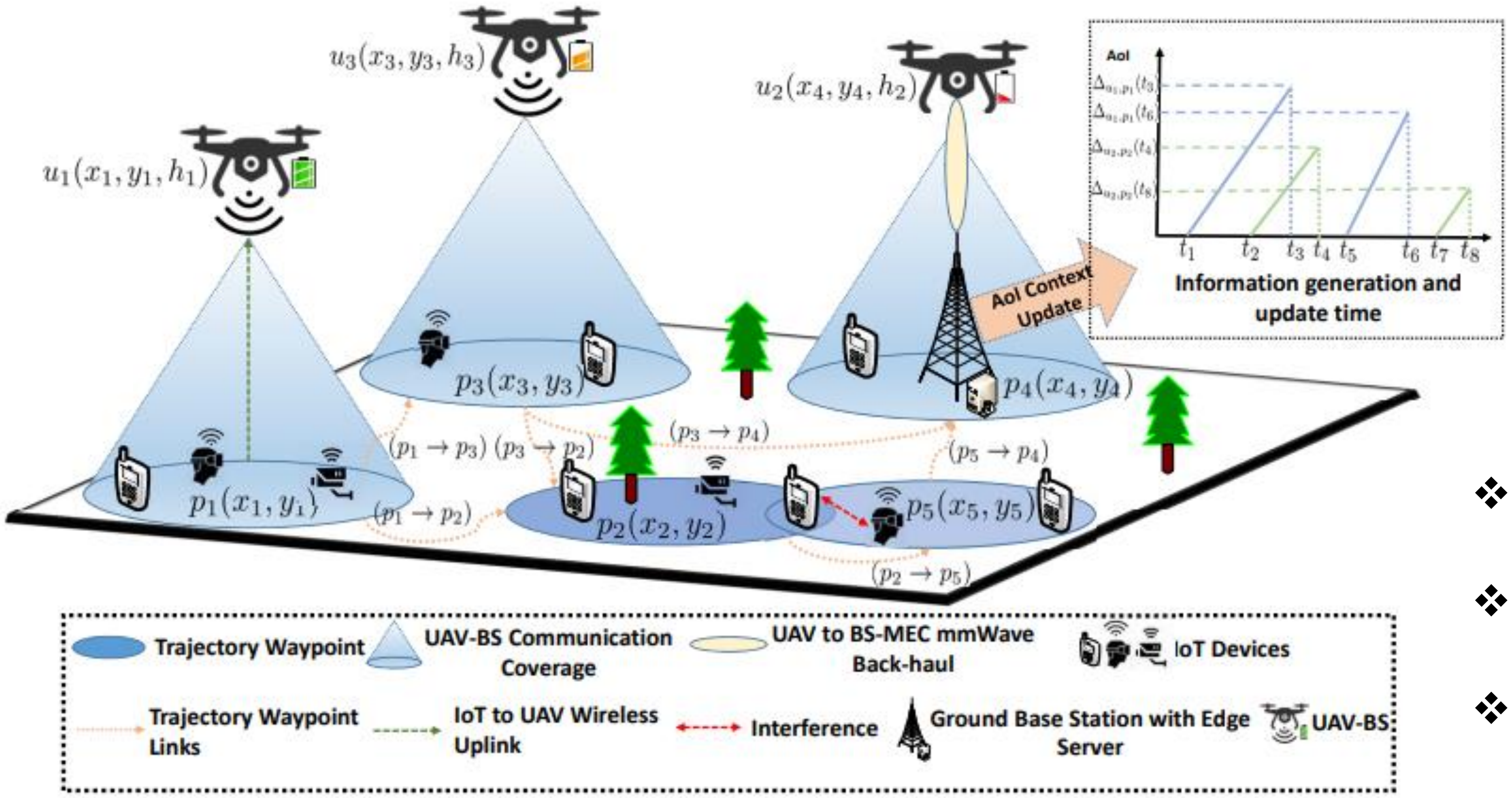

Fig. 1: System Model for Heterogeneous Unmanned Aerial Networks with Edge Computing

- Set of Trajectory points: $\mathcal{P} = \{1, 2, \cdots, P\}$
- Set of UAV-BSs: $\mathcal{U} = \{1, 2, \cdots, U\}$
- Set of IoT devices: $\mathcal{I} = \{1, 2, \cdots, I\}$

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- Probability of LoS and NLoS between UAV-BS and IoT device:

$$\zeta_{i,p}^{u} = \begin{cases} \frac{1}{1+\alpha \exp(-\hat{\alpha}(\frac{180}{\pi}\Theta_u - \alpha))}, & \text{LoS channel,} \\ 1 - \left[\frac{1}{1+\alpha \exp(-\hat{\alpha}(\frac{180}{\pi}\Theta_u - \alpha))}\right], & \text{NLoS channel.} \end{cases}$$

Elevation Angle

- Path Loss in decibel (dB):

Distance between UAV and UE

$$P_{i,p}^{u} = \begin{cases} 20\log(\frac{4\pi f_c \delta_{i,p}^{u}}{c}) + \epsilon, & \text{LoS channel,} \\ 20\log(\frac{4\pi f_c \delta_{i,p}^{u}}{c}) + \bar{\epsilon}, & \text{NLoS channel.} \end{cases}$$

Attenuation factors

- Signal to Interference pulse noise ratio

Interference

$$\gamma_{i,p}^{u}(t) = \frac{\hat{P}_{i,p}^{u}(10^{\frac{\zeta_{i,p}^{u}}{10}})^{-1}}{I_{i,p}^{u} + \sigma^2}.$$

Received signal power at UAV-BS:

$$I_{i,p}^{u} = \sum_{p'\in\mathcal{P}}\sum_{u'\in\mathcal{U}}\sum_{i'\in\mathcal{I}} \hat{P}_{i',p'}^{u'}(10^{\frac{\zeta_{i',p'}^{u'}}{10}})^{-1}$$

Channel Model

- Channel capacity at time 't':

Total IoT devices

Total bandwidth

$$r^{u}_{i,p}(t) = \begin{cases} \frac{\beta_u}{|\mathcal{I}|} \log\left(1+\gamma^{u}_{i,p}(t)\right), & \text{if } \gamma^{u}_{i,p}(t) > \gamma_{th}, \\ 0, & \text{otherwise.} \end{cases}$$

- The received power at ground BS 'b' from UAV-BS 'u' as:

$$\hat{P}_{b,u} = P^{tx}_{b,u} \cdot G^{tx}_{u} \cdot G^{rx}_{b} \left(\frac{c}{4\pi \delta_{b,u} f^{mmWave}_{c}} \right).$$

Distance between UAV-BS and round BS

mmWave carrier frequency

Transmit power of UAV-BS

Antenna gain of transmitter and receiver

- The channel capacity between UAV-BS and ground BS :

$$r^{mmWave}_{b,u}(t) = \begin{cases} \beta^{mmWave}_{b,u} \cdot \log\left(1 + \frac{\hat{P}_{b,u}}{\beta^{mmWave}_{b,u} \sigma^2}\right), \\ 0, \quad \text{otherwise.} \end{cases}$$

$$\delta_{u,b} = \sqrt{(x_u - x_b)^2 + (y_u - y_b)^2}$$

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Channel Model

- Transmission energy of UAV-BS while using backhaul link at time t:

$$E_u^{mmWave}(t) = P_{b,u}^{tx} \times r_{b,u}^{mmWave}(t).$$

- Total mobility energy cost of UAV:

$$E_u(t) = \delta_u(t) \times E_{prop}.$$

$$\tau_u(t) = [x_u(t), y_u(t)]^T$$

$$\delta_u(t) = \sqrt{h_u^2 + ||\tau_u(t)^2||}, 0 \leq t \leq T.$$

Horizontal Distance

$$E_{prop} = k_1||v||^3 + \frac{k_2}{||v||}\left(1 + \frac{||a||^2}{g^2}\right)$$

UAV propulsion energy

a: acceleration, v: velocity, g: Gravitational acceleration

- The total energy efficiency for UAV-BS covers trajectory points to serve IoT devices over times T:

$$\eta(\mathcal{P}, u) = \sum_{t=1}^{T} \sum_{p=1}^{|\mathcal{P}|} \frac{(r_{b,u}^{mmWave}(t) + \sum_{i=1}^{|\mathcal{I}|} r_{i,p}^{u}(t))}{(E_u^{mmWave}(t) + E_u(t))}. \quad (11)$$

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Problem Formulation

$$\underset{\{\mathcal{P}_u\}_{u\in\mathcal{U}}}{\arg\max} \sum_{u\in\mathcal{U}} \eta(\mathcal{P}_u, u), \quad (14)$$

Maximize Energy Efficiency of UAV-BS

subject to

$$\bigcap_{u\in\mathcal{U}} \mathcal{P}_u = \{b\}, \forall u \in \mathcal{U}, \quad (15)$$

Non-Overlapping trajectories of UAV-BSs except ground BS

$$\bigcup_{u\in\mathcal{U}} \mathcal{P}_u = \mathcal{P}, \forall u \in \mathcal{U}, \quad (16)$$

All trajectories points are covered

$$\eta(\mathcal{P}_u) \geq \eta_{th}, \forall u \in \mathcal{U}, \quad (17)$$

Energy Efficiency constraint

$$\hat{\Delta}_b(\mathcal{P}_u) \leq \hat{\Delta}_b^{th}, \forall p \in \mathcal{P}_u \backslash \{b\}. \quad (18)$$

AoI constraint

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Proposed Solution

- We deploy the Deep Q- Learning to solve problem (14)

- The state space for trajectory:

Energy Efficiency

Average AoI for navigation optimization

$$\mathcal{S} = \{s_t = (p^u_{current}, p_{end}, \eta, \Delta) | \eta \in [0, \eta_{th}], \Delta \in [1, \hat{\Delta}_b^{th}]\}$$

Current Positions

Target Position

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Proposed Solution

- The action space of UAV-BS is the trajectory planning each of the UAV-BS's navigation from one feasible state (i.e., position) to the next state while satisfying the trajectory and communication constraints.

- The learning agent selects an action a_t from the available actions upon state s_t:

$$a_t \in \mathcal{A}_{s_t} \subset \mathcal{A}, \quad \mathcal{A} = \{a_1, \cdots, a_U\} = \{\mathcal{P}_u\}_{u \in \mathcal{U}}$$

- At each state transaction, the agent receives the immediate reward which is used to form the trajectory control policy for navigation:

Reward

$$R_t = \begin{cases} \alpha_1 \eta(a_t), \text{if contraints (15)-(18) of (14) are true,} \\ -\alpha_1, \text{if contraints (15)-(17) of (14) are violated,} \\ 0, \quad \text{if contraints (15)-(18) of (14) is violated.} \end{cases} \tag{19}$$

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- The objective of the learning agent over T time slot is to maximize the future reward:

$$\boxed{\hat{R}(s,a;t) = \sum_{t_0=0}^{T} \gamma(t_0) \times R_t(t-t_0), \qquad (20)}$$

reflecting the trade-off between the importance of immediate and future rewards : [0, 1]

- Q-function or action value function is defined as: Transaction probability

$$\boxed{Q^{\pi}(s,a) = \hat{R}(s,a) + \gamma \sum_{s \in \mathcal{S}} P_{s,s'} V^{\pi}(s'), \qquad (21)}$$

Discounted cumulated state function

π' Control policy

- Goal is to obtain the best control policy. Therefore, the maximum Q-function is:

$$\boxed{Q^{\pi^{opt}}(s,a) = \mathbb{E}\big[R + \gamma \max_{a'} Q^{\pi^{opt}}(s',a')|s,a\big], \qquad (22)}$$

$$\boxed{V^{\pi^{opt}}(s) = \max_{a'} \big[Q^{\pi^{opt}}(s,a)\big].}$$

Learning rate

- To derive the optimal control policy, the Q- function is updated as:

$$\boxed{Q_{t'}(s,a) = Q_t(s,a) + \psi\big(R + \gamma\big[\max_{a'} Q_t(s',a')\big] - Q_t(s,a)\big), \qquad (24)}$$

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Proposed Solution

Algorithm 1: DQN with experience replay for UAV-BS Trajectory Policy Optimization for Navigation

```
Step 1: Initialization
Initialize Q(s, a; θ), M, target DQN parameters θ⁻ and
  construct DQN
Step 2: Training DQN with experience replay
for e = 1, ···, E do
    Initialize S
    for t = 1, ···, T do
        Calculate the energy efficinecy metric of the
          UAV-BSs using (11)
        Calculate instant reward R_t using (19)
        Select action a_t with given probability ε.
        Observe instant reward R_t and next state s_t'
        Store experience (s_t, s_t', a_t, R_t, R_t') in the
          experience replay memory M
        Randomly sample minibatch of experiences from
          M
        Adopt stochastic gradient descent (SGD) to train
          the DQN using loss function in (24)
        Update θ and Q(s, a; θ)
Store the Q-network
Step 3: Testing UAV-BS trajectory policy for
  UAV-BS navigation
Load the stored Q-network of Step 1
Retrieve R_t of the UAV-BSs at time slot t
Retrieve and select joint UAV-BS action
  a_t = max_{a_t} Q^{π^opt}(s_t, a; θ)
Update trajectory of UAV-BSs based on joint action
  index and target values of DQN
```

$$\mathcal{L}(\theta) = \mathbb{E}_{(s,a,r,s')\sim U(\mathcal{M})}\Big[\big(R + \gamma \max_{a'} Q^{\pi^{opt}}(s', a'; \theta^-) - Q(s, a; \theta)\big)^2\Big]. \quad (24)$$

Building Q- Network

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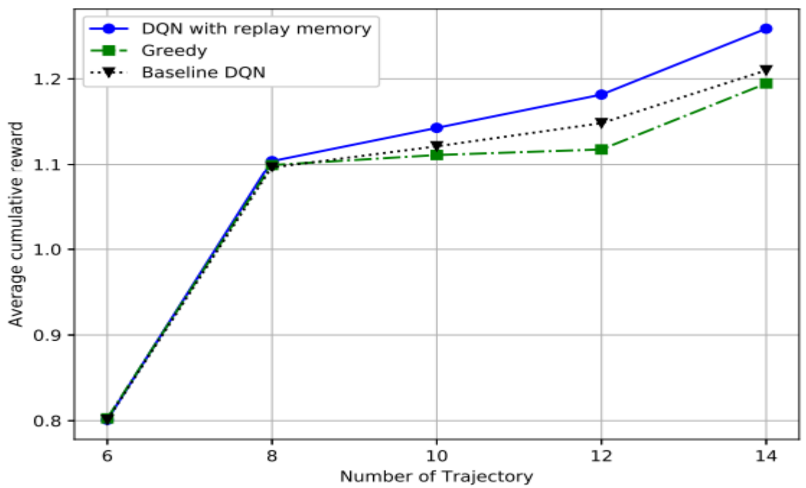

Fig. 2: Average cumulative reward comparison between the proposed approach and the baseline approaches over different numbers of trajectory way-points.

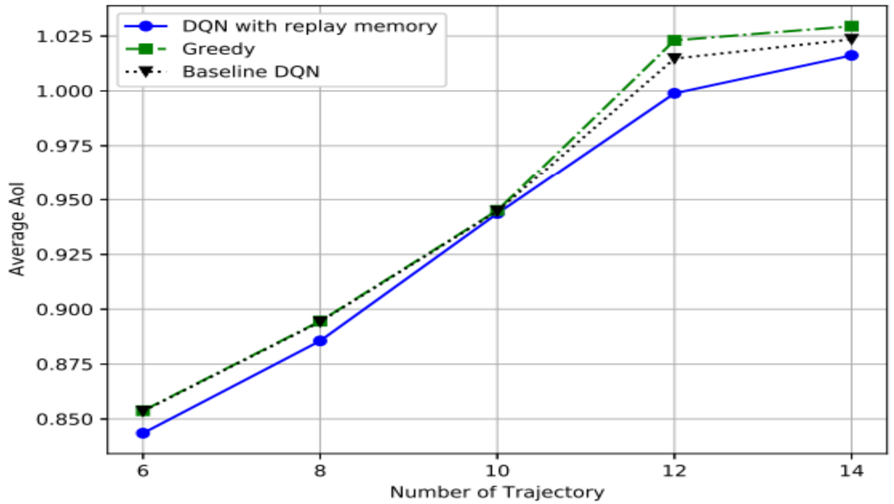

Fig. 3: Average AoI comparison between the proposed approach and the baseline approaches over different number of trajectory way-points.

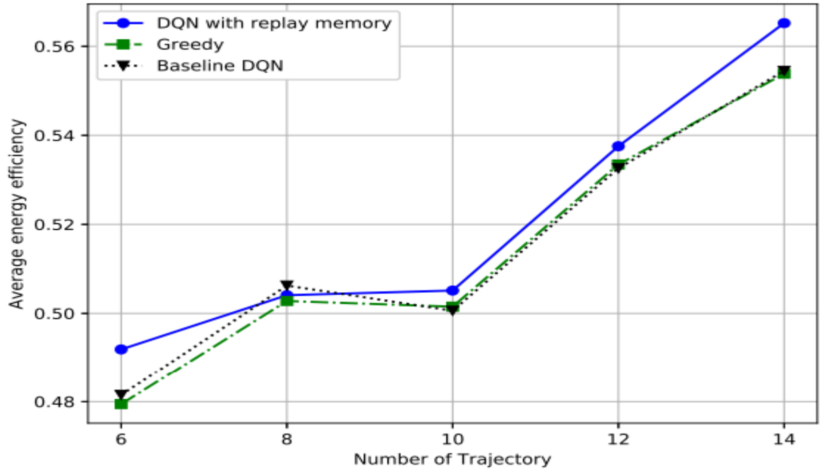

Fig. 4: Average energy efficiency comparison between the proposed and the baseline approaches over different number of trajectory way-points.

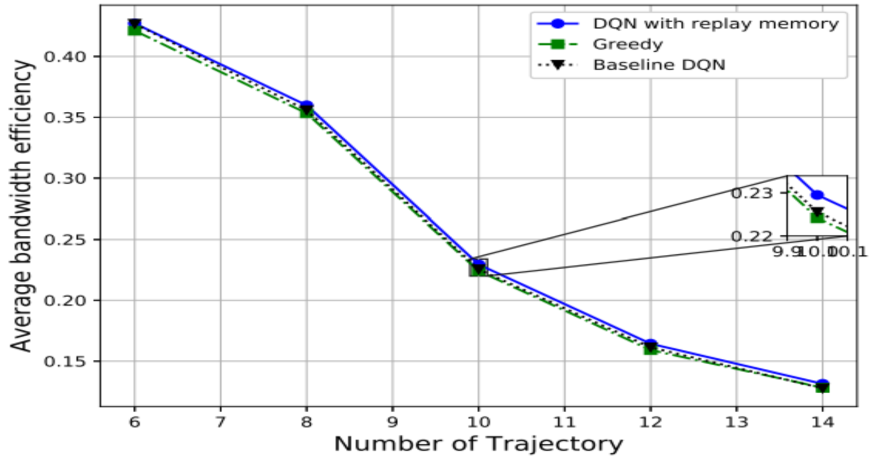

Fig. 5: Average bandwidth efficiency comparison between the proposed and the baseline approaches over different number of trajectory way-points.

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Summary

- We focused on developing the UAV-BS navigation policy to improve data freshness and accessibility to the IoT network.
- An agile deep learning reinforcement with an experience replay model that is well-suited to solving the energy-efficient UAV-BS navigation problem under trajectory and AoI constraints
- The numerical results also confirmed that effectiveness of the proposed DQN with experience replay memory under different network conditions

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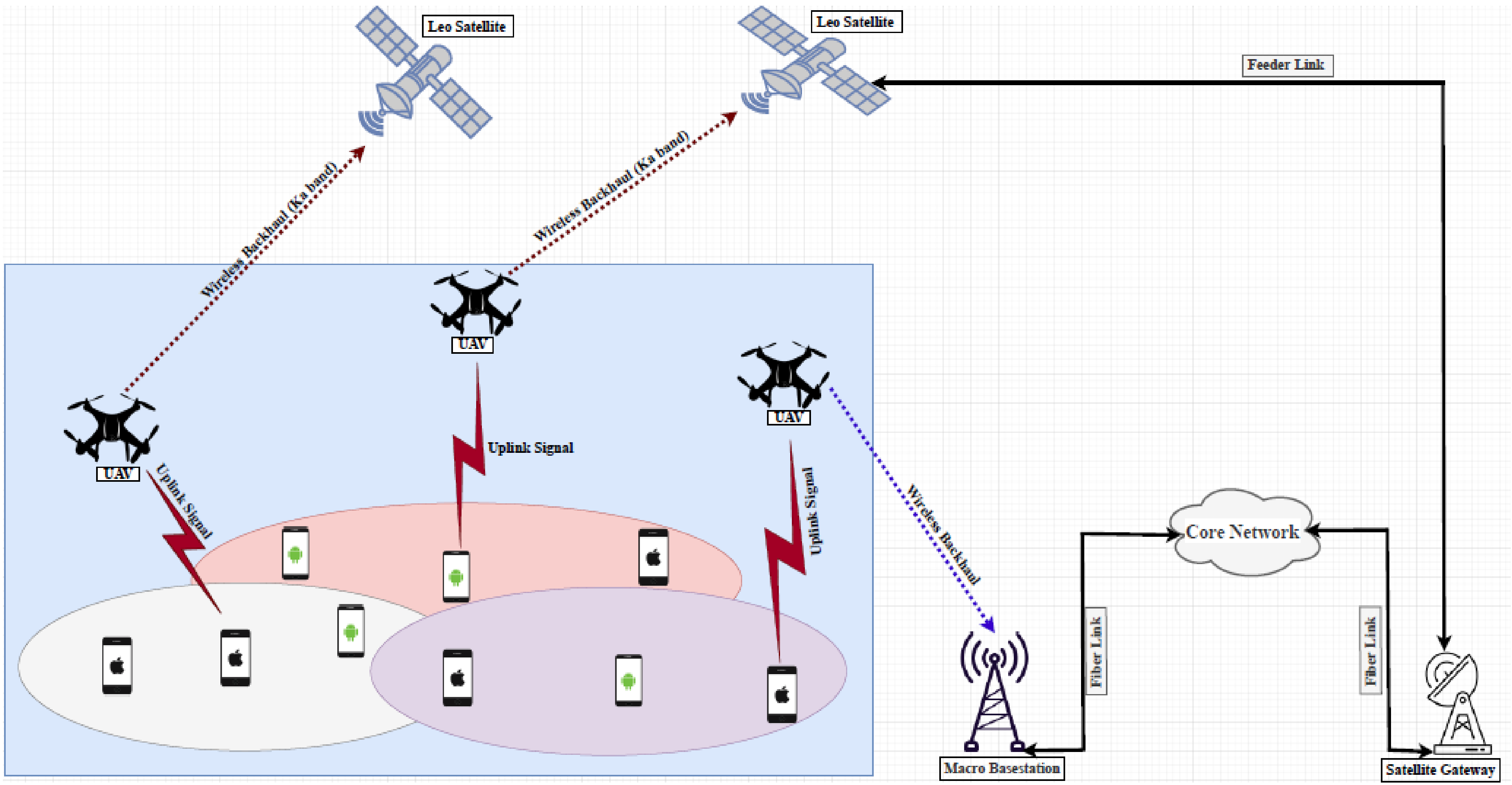
Challenges and Ongoing Research

Challenges and Ongoing Research

- Currently, researchers in both academic and industry are trying to deploy not only UAV-Assisted wireless network but also integrate Space-air-ground (satellite-UAV-BS) network



Challenges and Ongoing Research

- There are still several challenging issues which are under unexplored:

  - The optimal deployment of UAVs to get the maximum coverage area and strong wireless signal strength with low co-channel interference.

  - Controlling the trajectory of the UAVs to make sure the safety distance between UAVs and the optimal resources (i.e., bandwidth, and power) allocation to get the maximum data rate by taking into account the energy constraint of the UAVs.

  - Considering the optimal user association with the UAVs to achieve the highest rate.

  - Space-Air-Ground channel modeling.

Thanks for your attention!!!

- Q&A