“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
  - 3TO: THz-Enabled Throughput and Trajectory Optimization of UAVs in 6G Networks
  - Satellite-based ITS Data Offloading & Computation in 6G Networks
- Challenges and Ongoing Research

- 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) and Satellites 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 67.9% of world population can get internet access in till 2023. So, how about the remaining 32.1 % ????

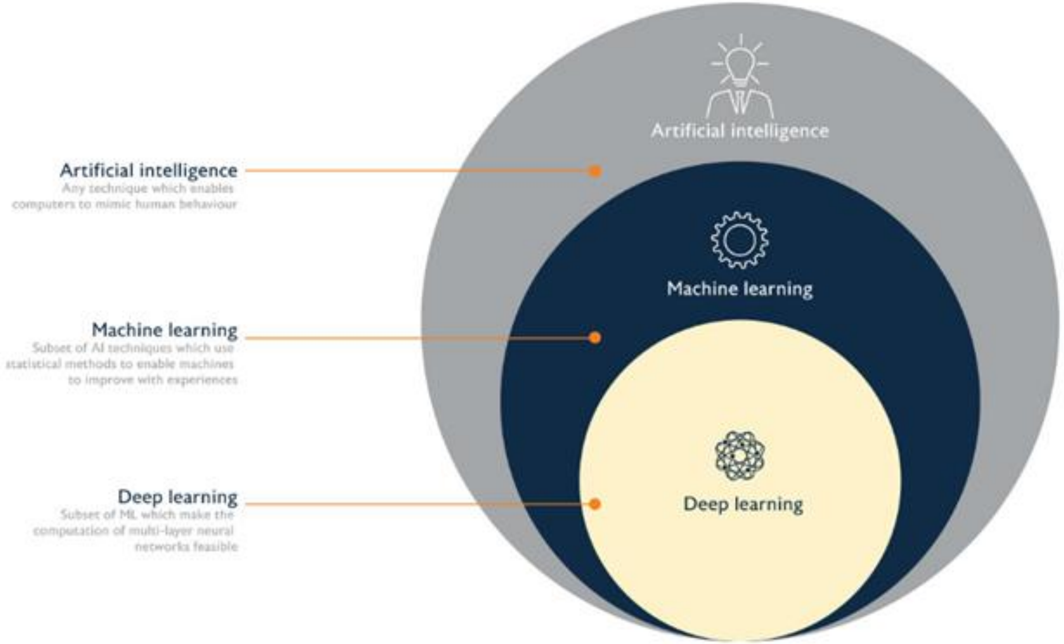
WORLD INTERNET USAGE AND POPULATION STATISTICS
2023 Year Estimates

World Regions	Population (2022 Est.)	Population % of World	Internet Users 31 Dec 2021	Penetration Rate (% Pop.)	Growth 2000-2023	Internet World %
Africa	1,394,588,547	17.6 %	601,940,784	43.2 %	13,233 %	11.2 %
Asia	4,352,169,960	54.9 %	2,916,890,209	67.0 %	2,452 %	54.2 %
Europe	837,472,045	10.6 %	747,214,734	89.2 %	611 %	13.9 %
Latin America / Carib.	664,099,841	8.4 %	534,526,057	80.5 %	2,858 %	9.9 %
North America	372,555,585	4.7 %	347,916,694	93.4 %	222 %	6.5 %
Middle East	268,302,801	3.4 %	206,760,743	77.1 %	6,194 %	3.8 %
Oceania / Australia	43,602,955	0.5 %	30,549,185	70.1 %	301 %	0.6 %
WORLD TOTAL	7,932,791,734	100.0 %	5,385,798,406	67.9 %	1,392 %	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 or Satellites 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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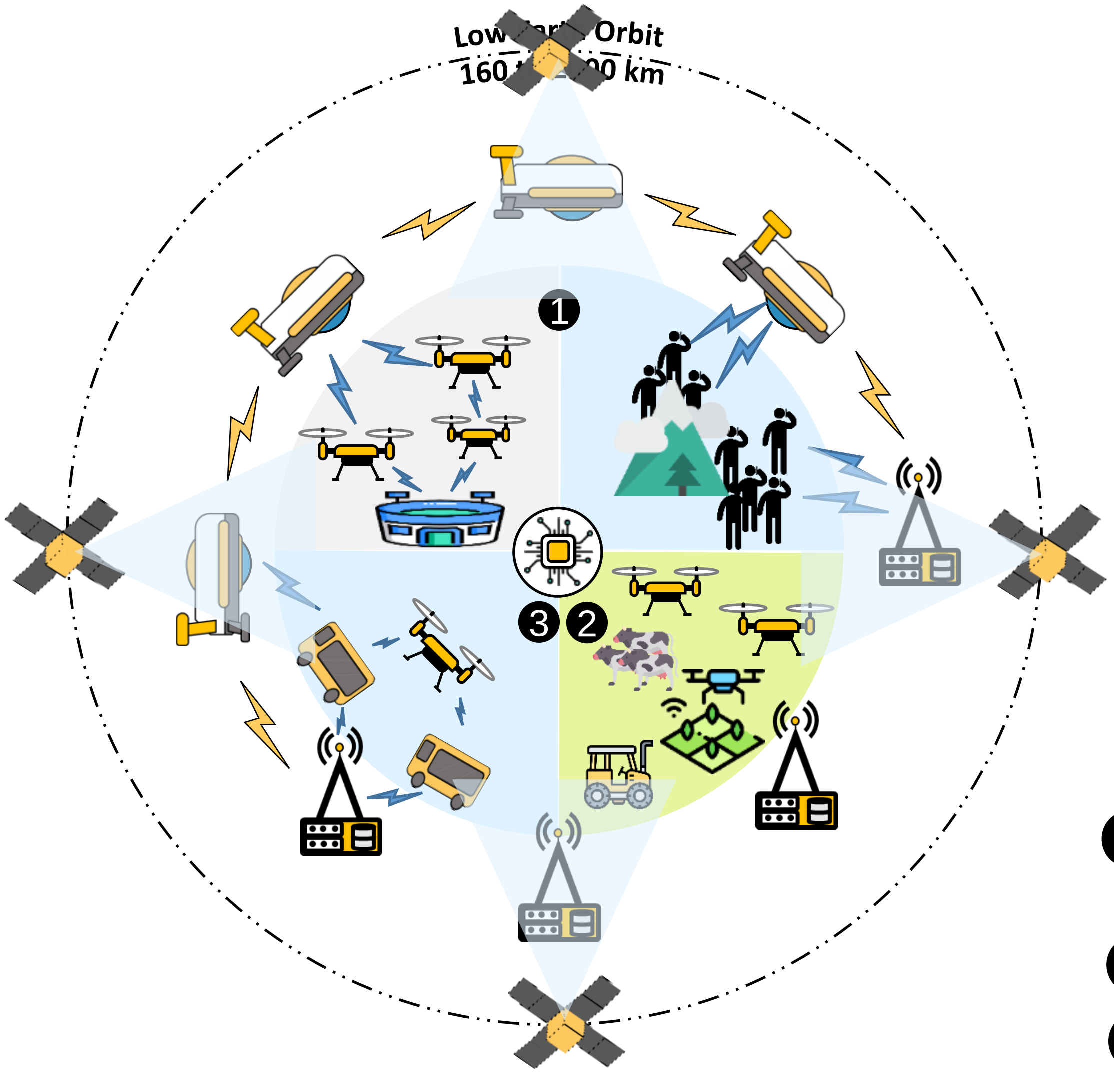
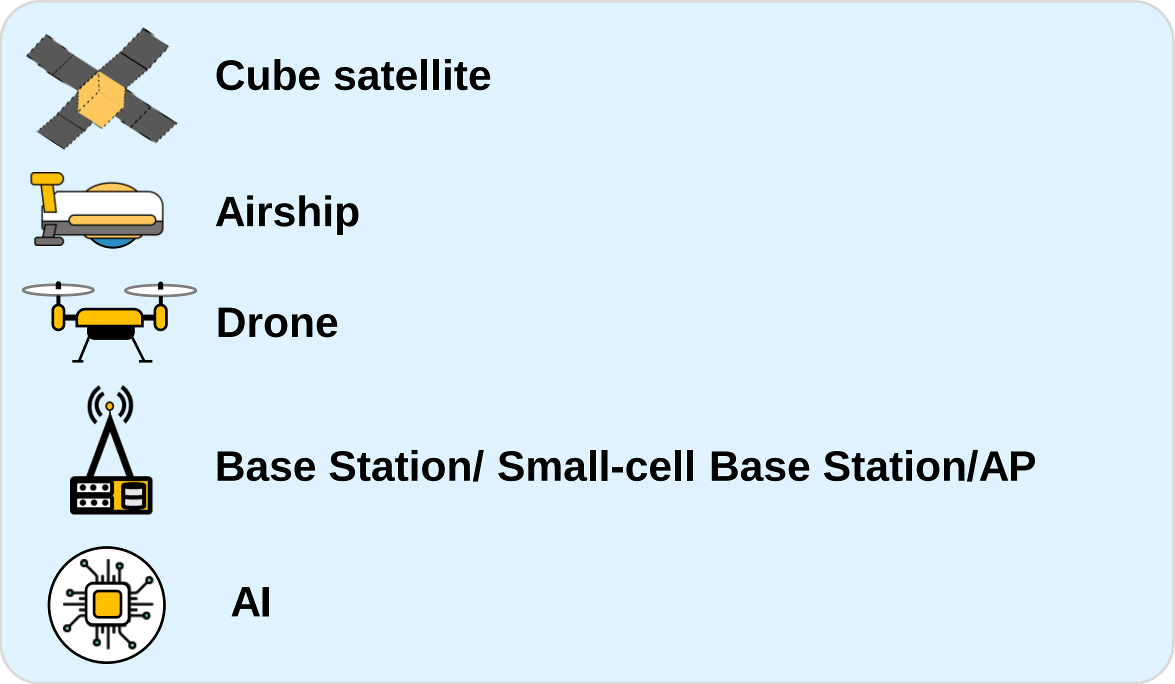
UAV-Assisted Wireless Networks: The Concept and Challenges

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

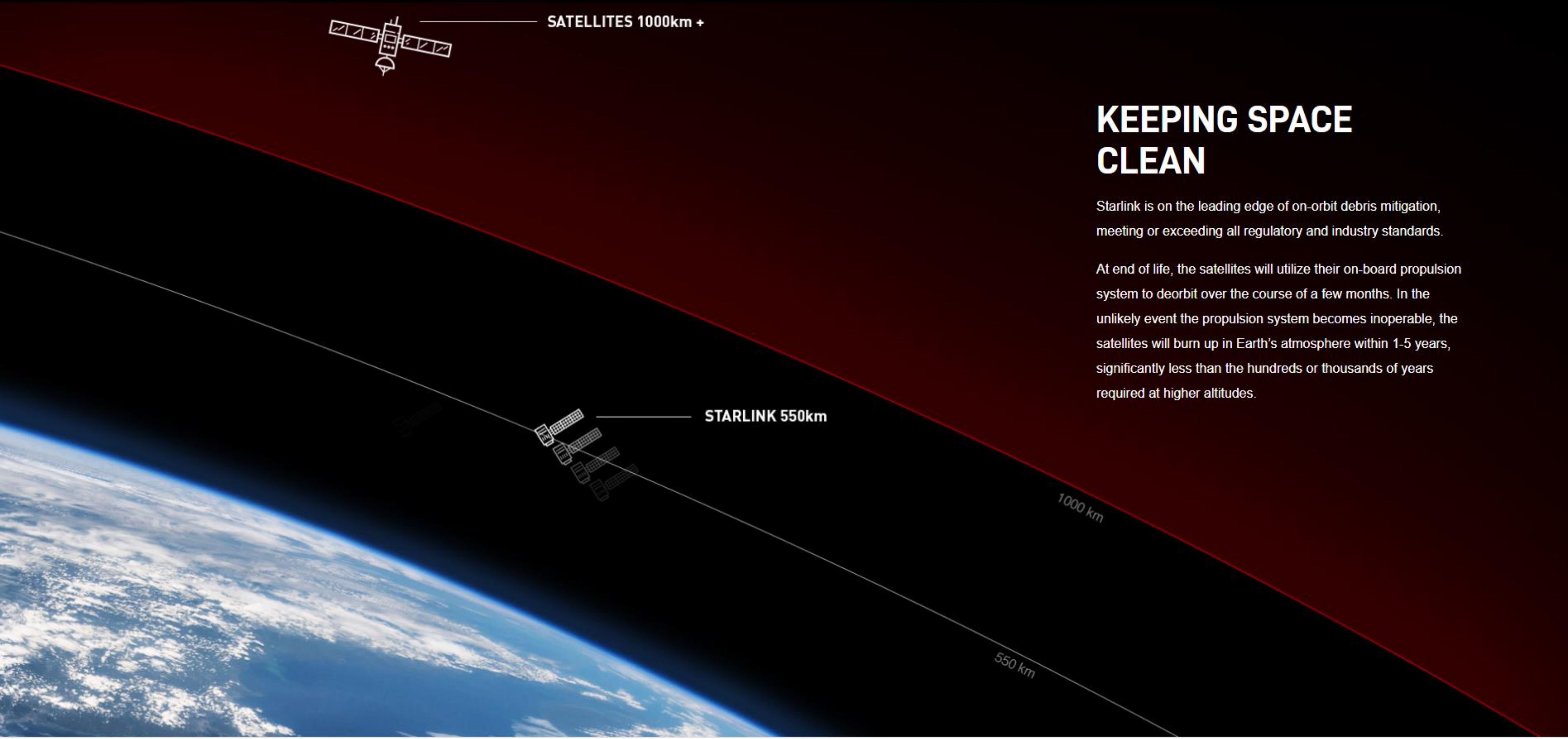
UAV-Assisted Wireless Networks Overview





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)

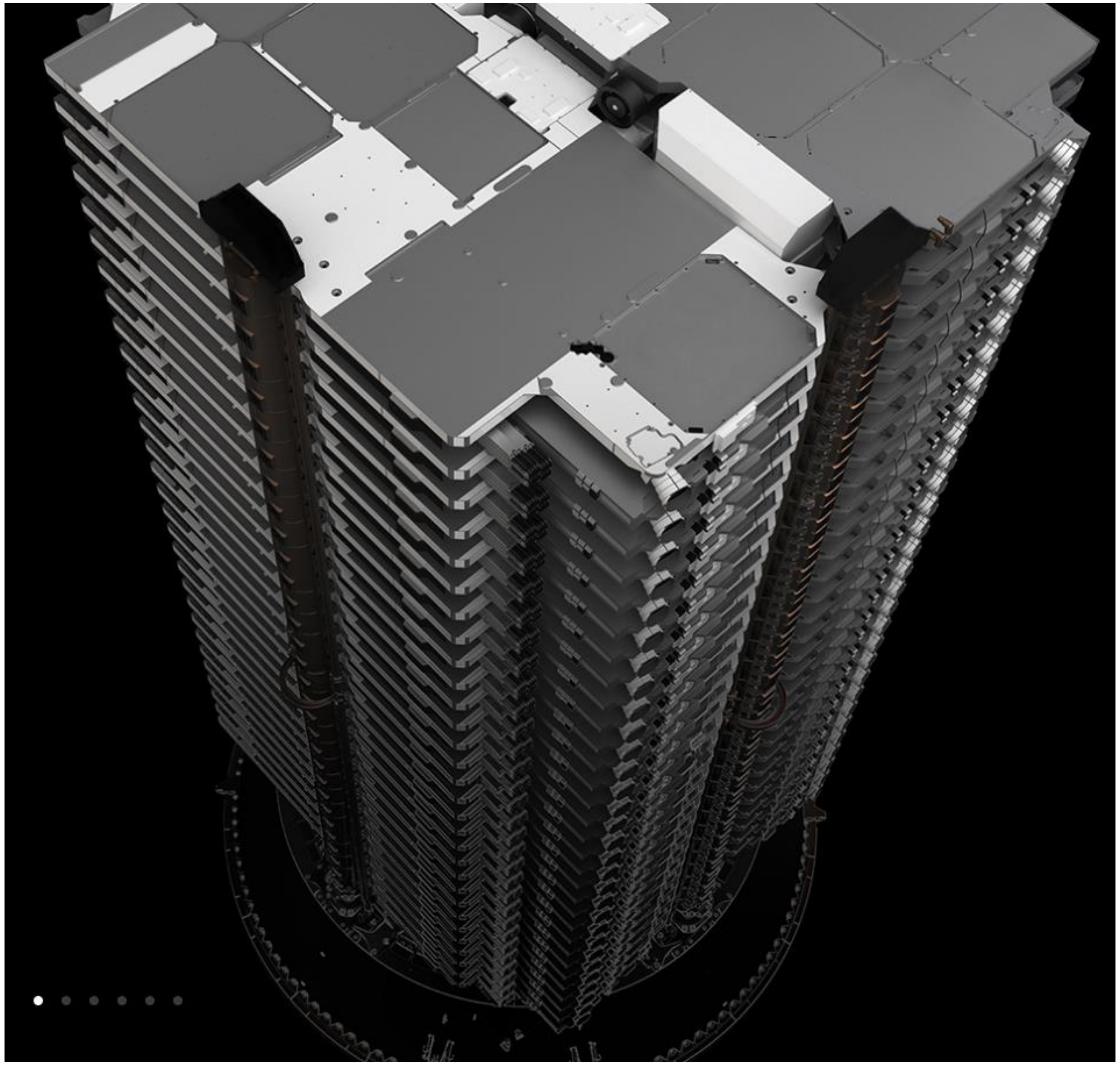


https://www.starlink.com/

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 can Starlink internet be available?

- launched 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.

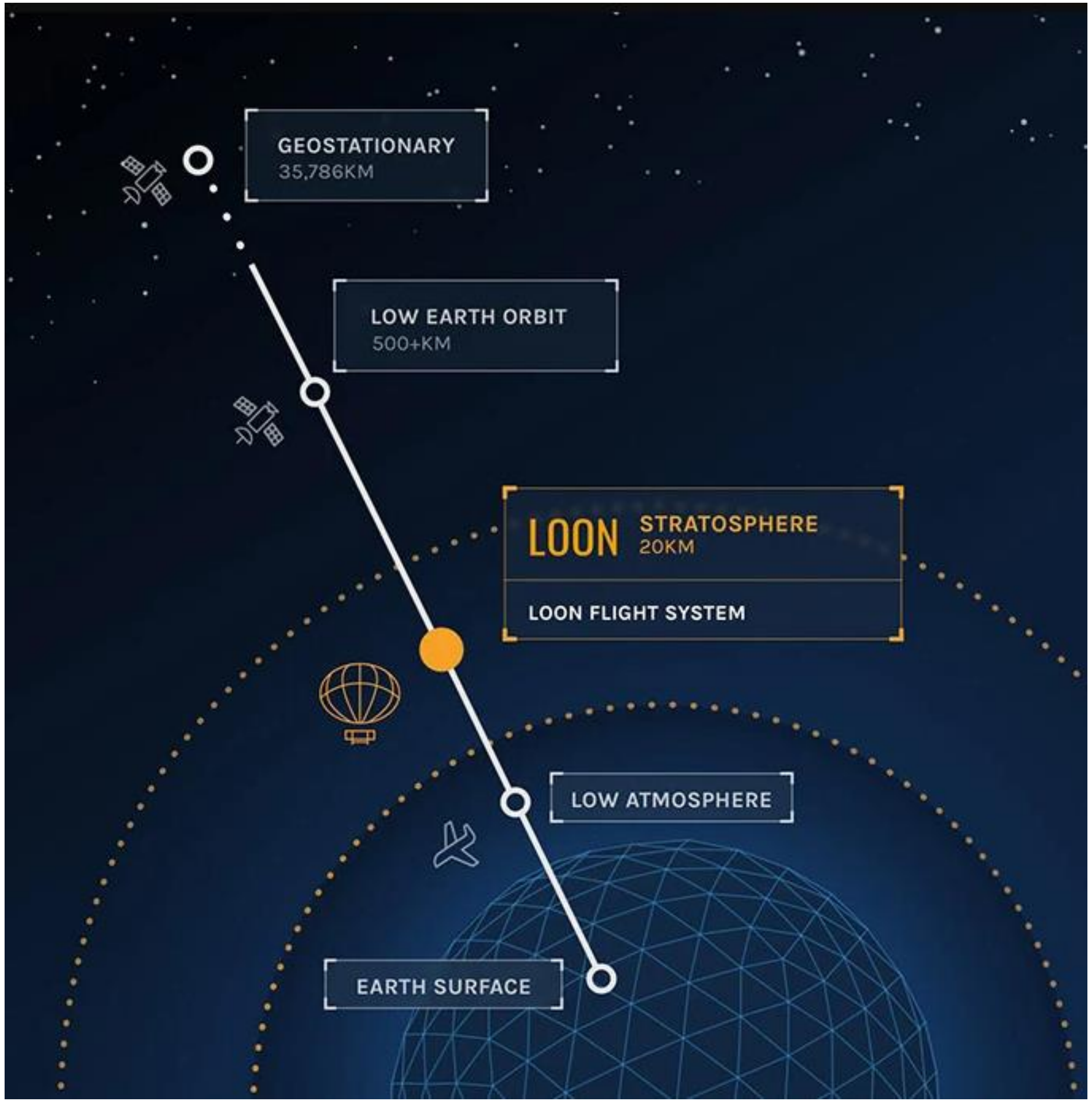
  - Transmissions from satellite to user terminals: 10.7 – 12.7 GHz and 37.5 – 42.5 GHz
  - Satellite to gateway transmissions: 17.8 – 18.6 GHz and 18.8 – 19.3 GHz and 37.5 – 42.5 GHz
  - Transmissions from terminals to satellites: 14.0 – 14.5 GHz and 47.2 – 50.2 GHz and 50.4 – 51.4 GHz
  - Transmissions 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

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

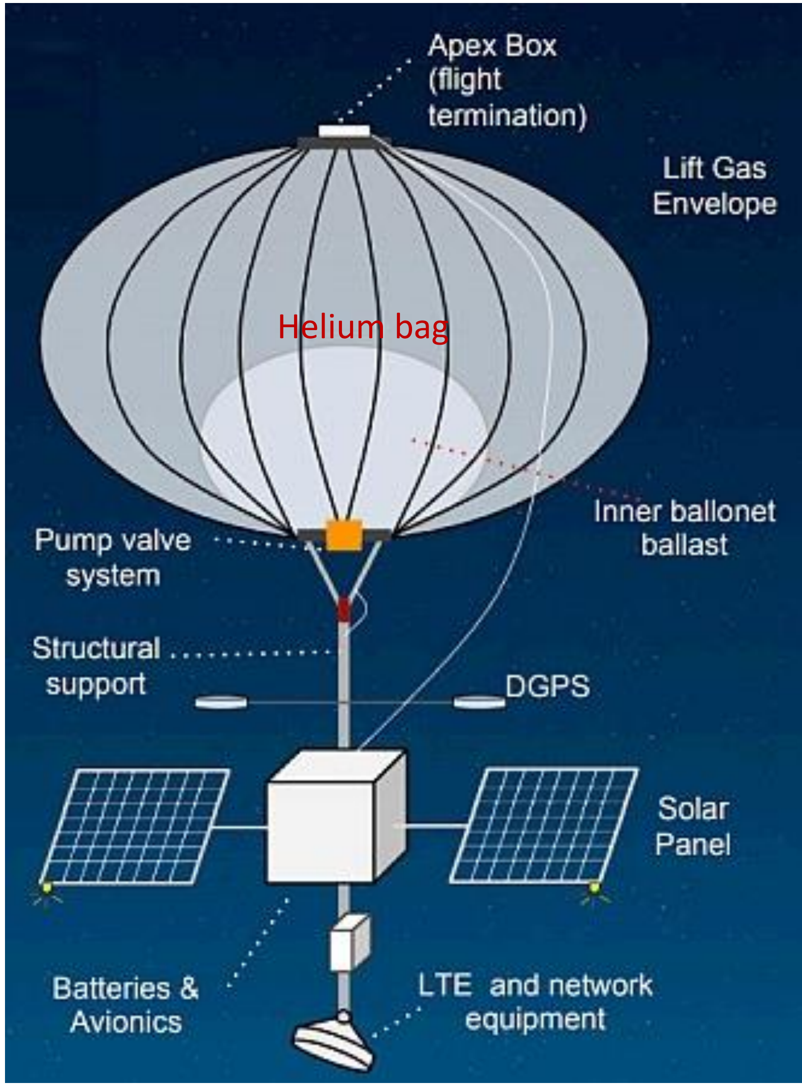
Goolge's Project Loon: A network of balloons travelling on the edge of space is designed to connect people in rural and remote areas, helping fill coverage gaps, and brining people back online after natural disasters.

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



The Loon Flight System consists of :

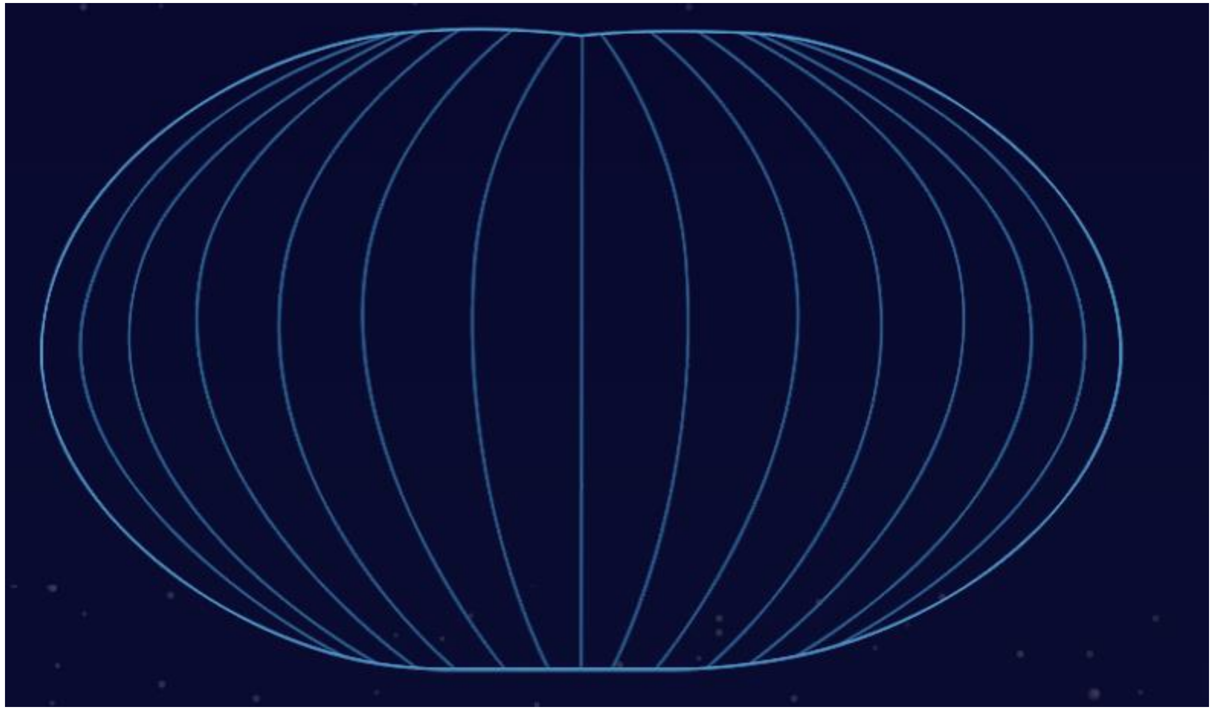
1. Balloon envelope
2. Bus
3. The payload



DGPS: Differential Global Positioning Systems

https://loon.com/technology/

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

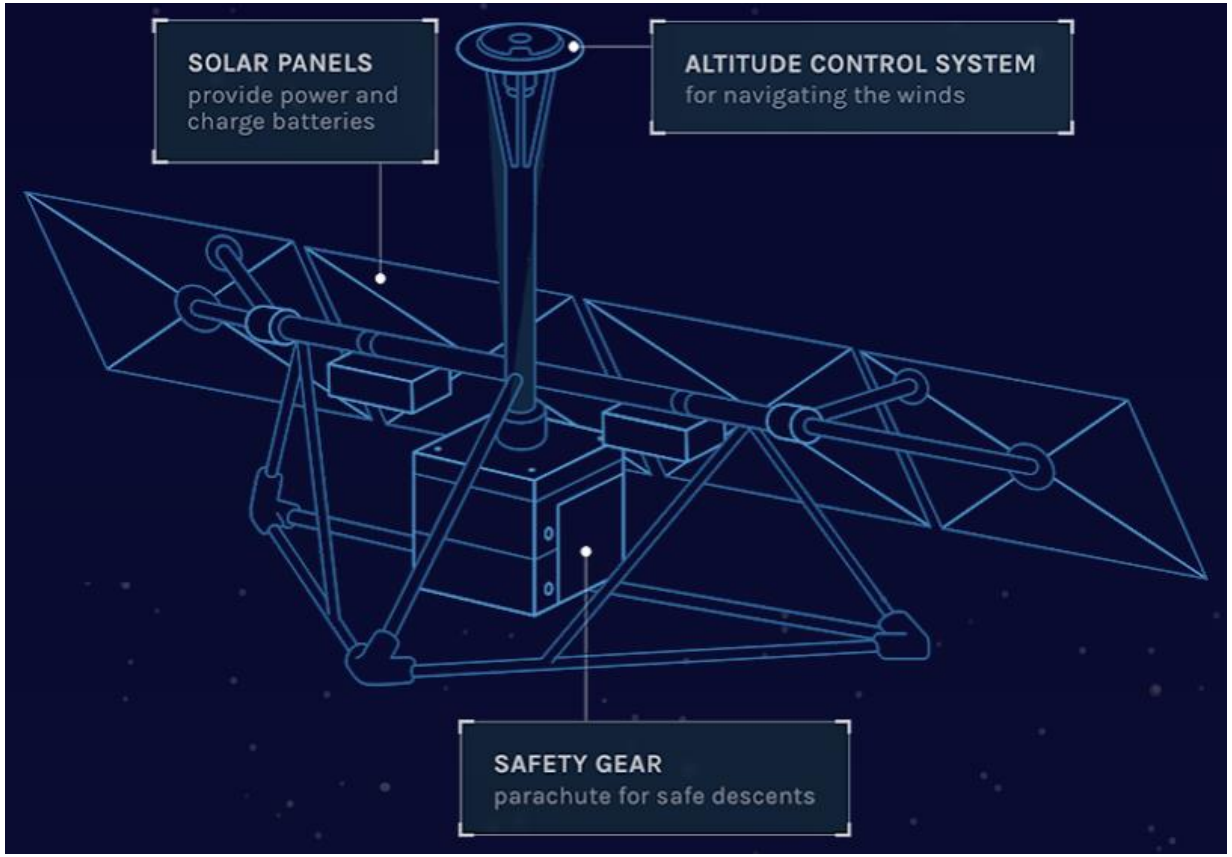


Balloon Envelope

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. The balloons are built to last for hundreds of days before landing back on Earth in a controlled descent.

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

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

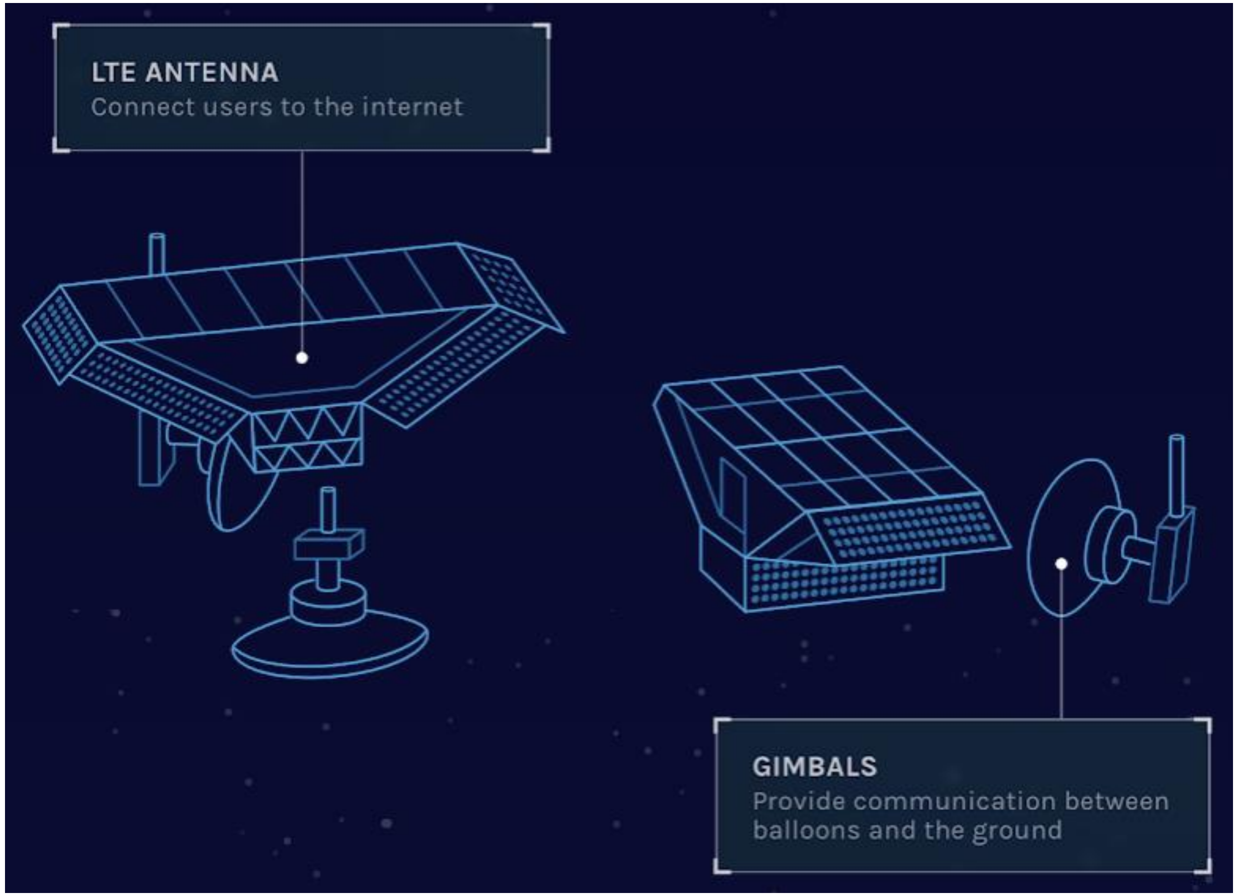


Bus

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)

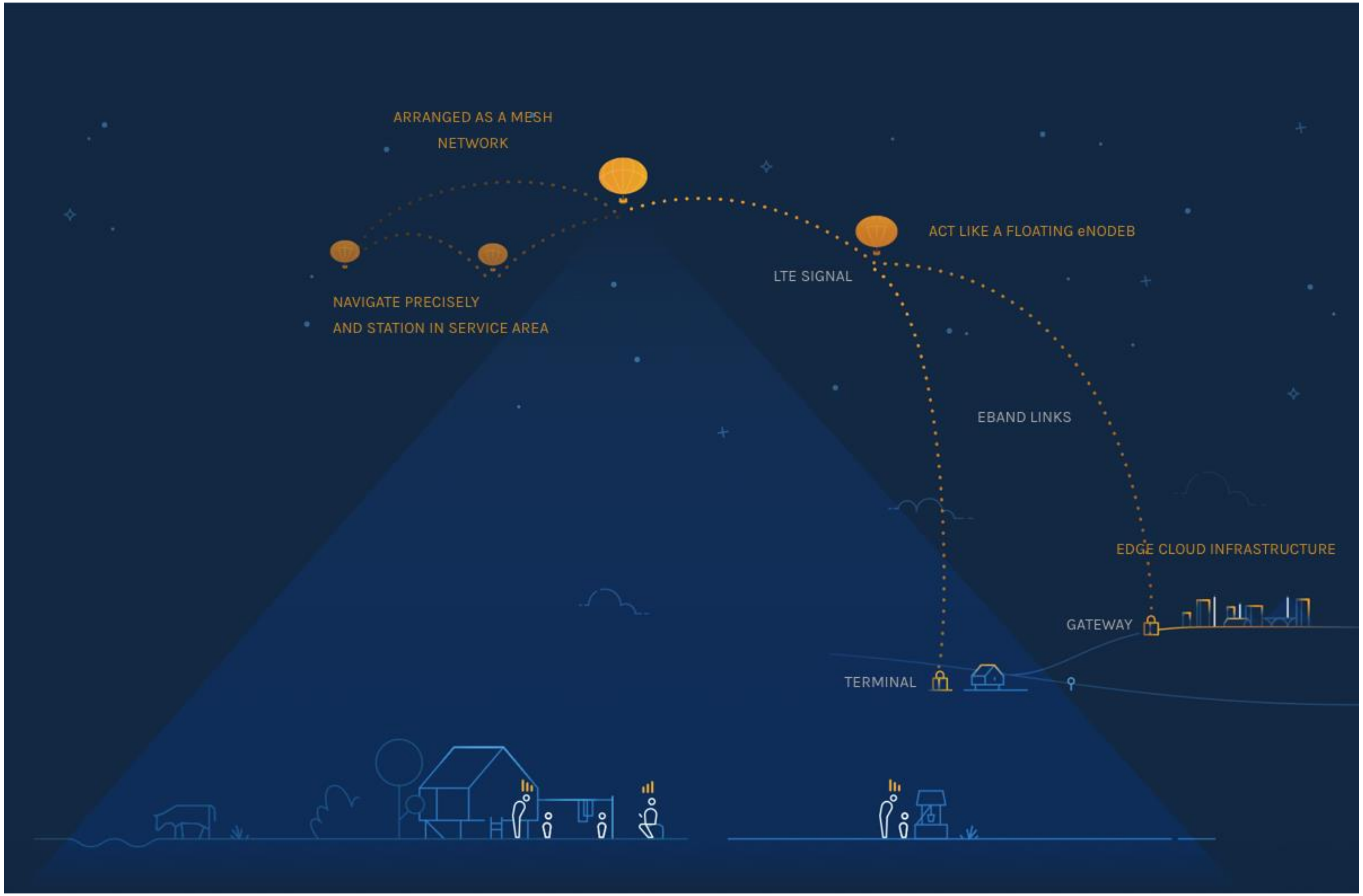


Payload

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.

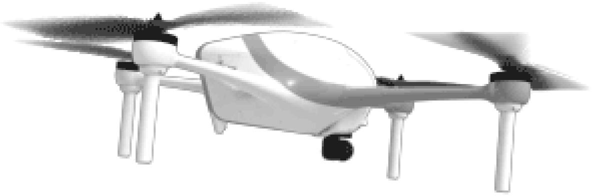
https://loon.com/technology/flight-systems/

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



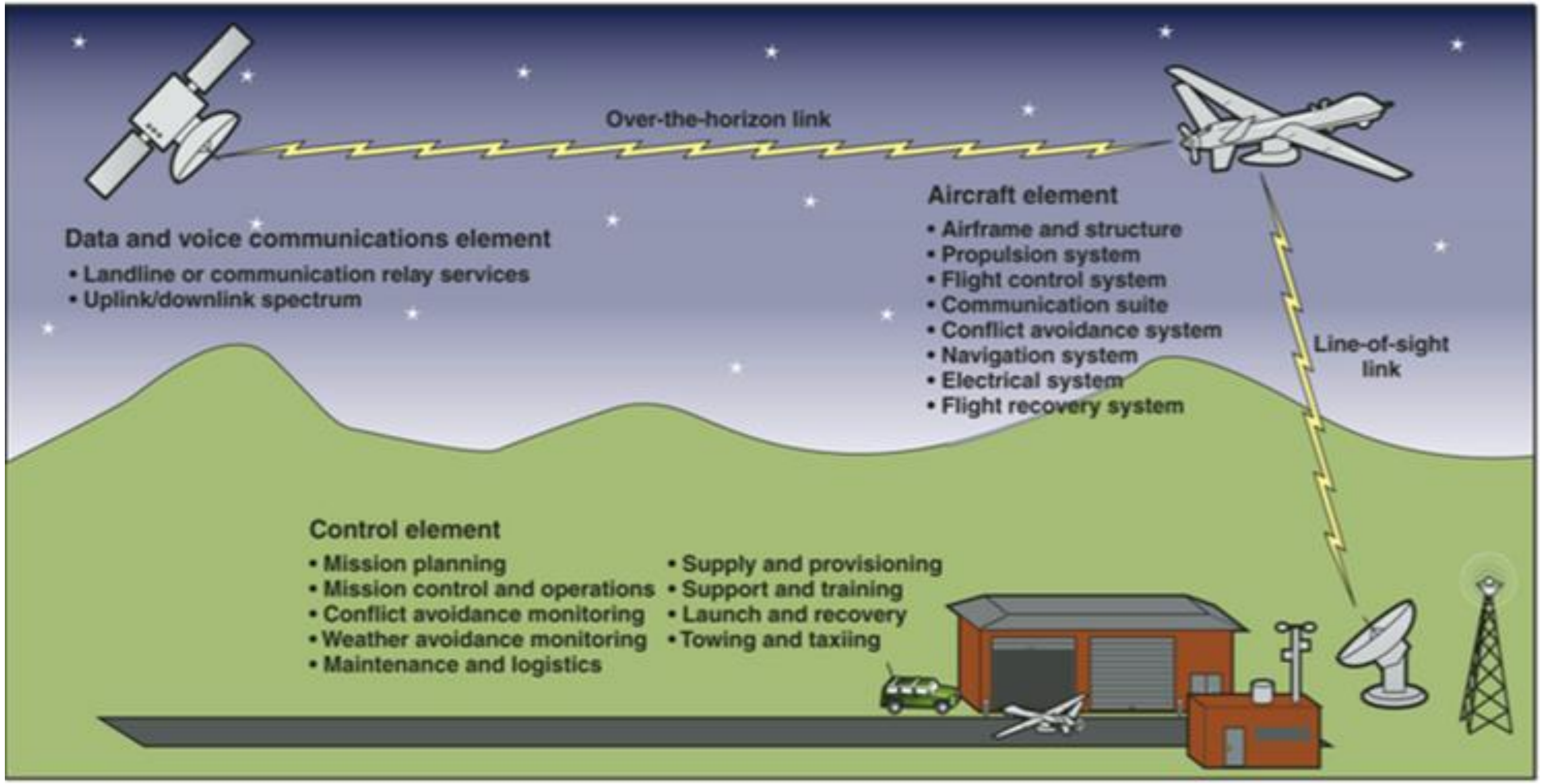
Rotary Wing UAV

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

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.

Conceptual Rendering of Unmanned Aircraft System



https://itlaw.fandom.com/wiki/Unmanned_aircraft_system

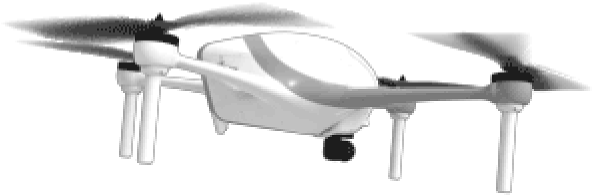
What is an Autonomous Drone?

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

DRONE INDUSTRY INSIGHTS

THE 5 LEVELS OF DRONE AUTONOMY

Autonomy Level	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Human Involvement						
Machine Involvement						
Degree of Automation	No Automation	Low Automation	Partial Automation	Conditional Automation	High Automation	Full Automation
Description	Drone control is 100% manual.	Pilot remains in control. Drone has control of at least one vital function.	Pilot remains responsible for safe operation. Drone can take over heading, altitude under certain conditions.	Pilot acts as fall-back system. Drone can perform all functions 'given certain conditions'.	Pilot is out of the loop. Drone has backup systems so that if one fails, the platform will still be operational.	Drones will be able to use AI tools to plan their flights as autonomous learning systems.
Obstacle Avoidance	NONE	SENSE & ALERT	SENSE & ALERT	SENSE & AVOID	SENSE & NAVIGATE	SENSE & NAVIGATE

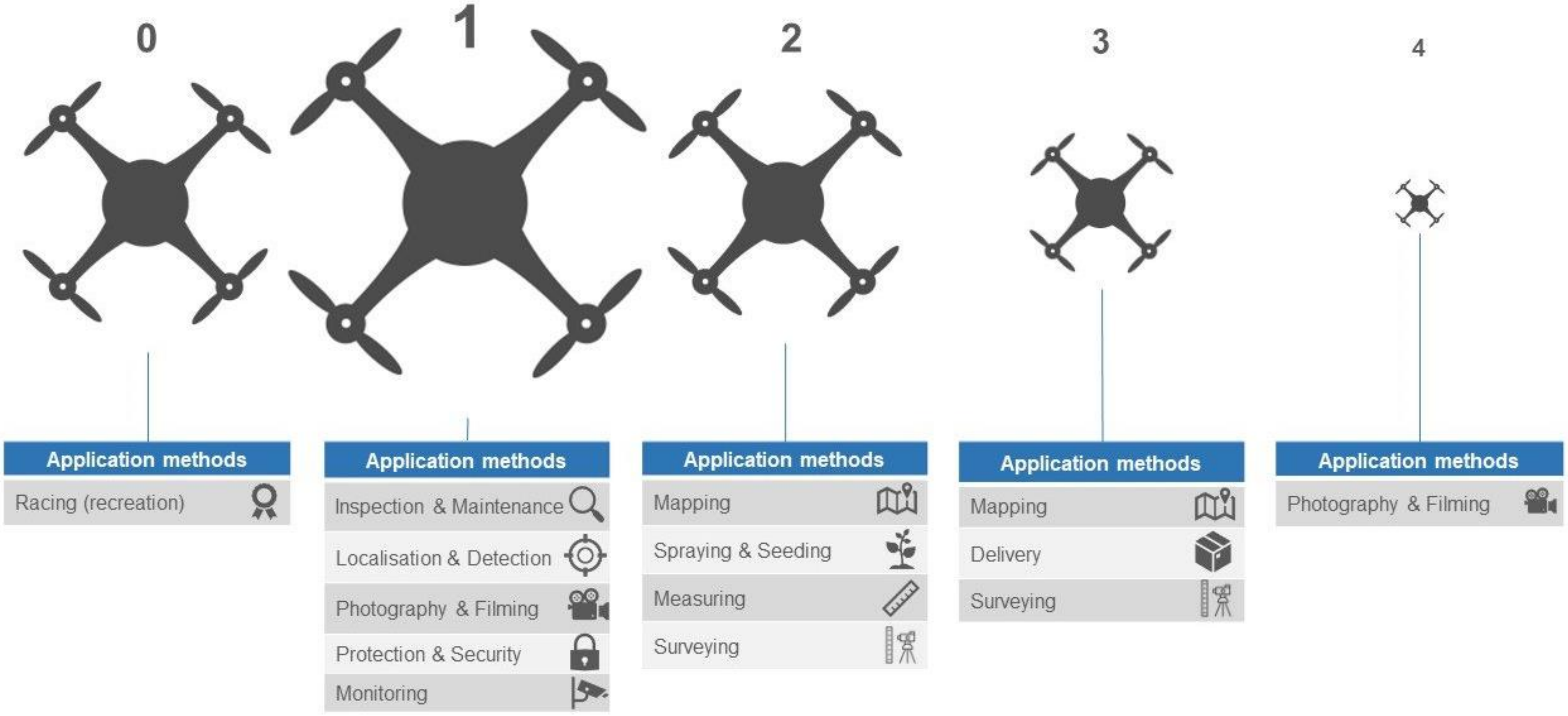
Source: DRONEII.com

Date: March 12th 2019

DRONEII.COM
DRONE INDUSTRY INSIGHTS

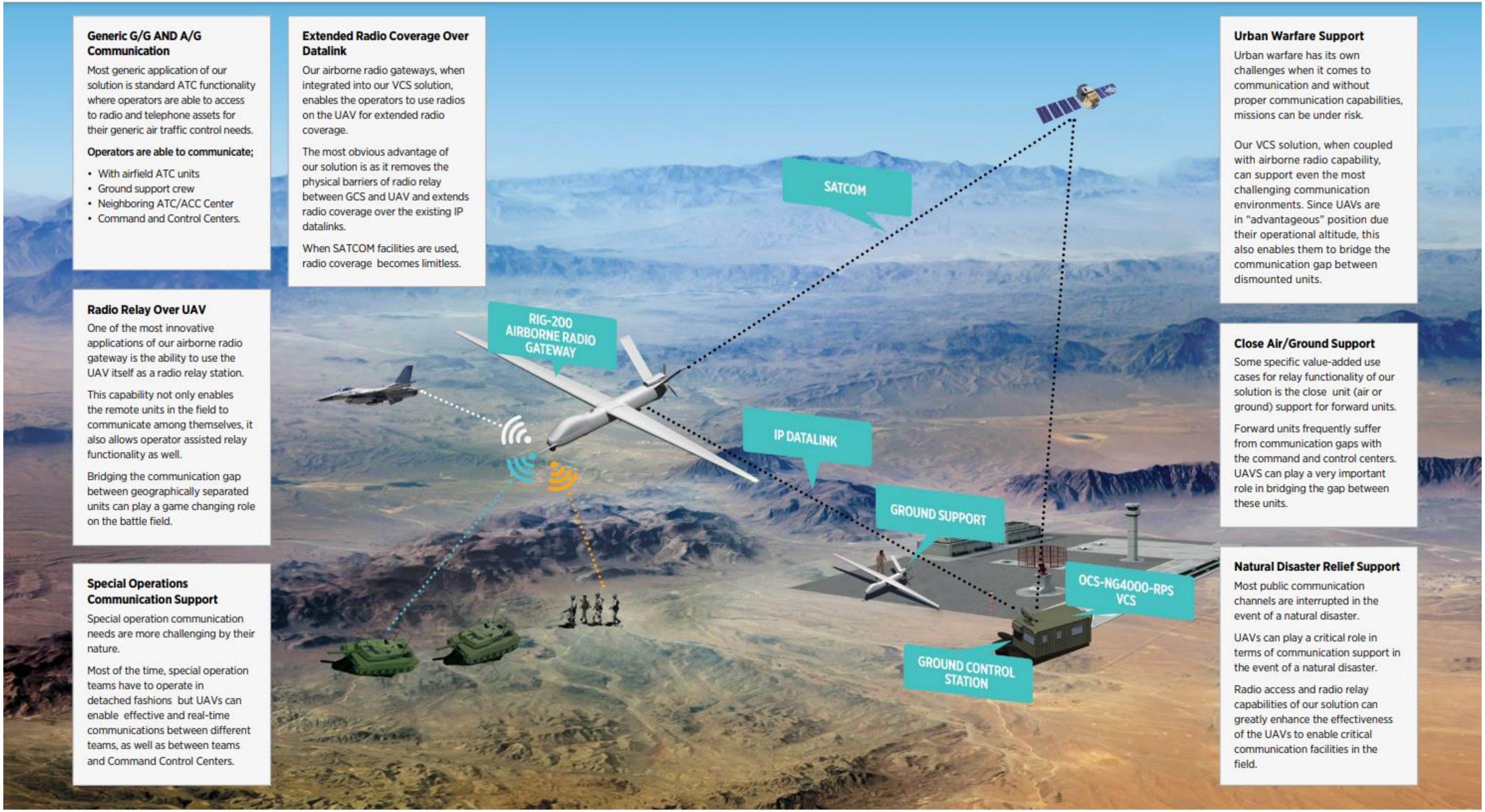
https://dronelife.com/2019/03/11/droneii-tech-talk-unraveling-5-levels-of-drone-autonomy/

Types of UAVs: Levels of Autonomy & Drone Applications



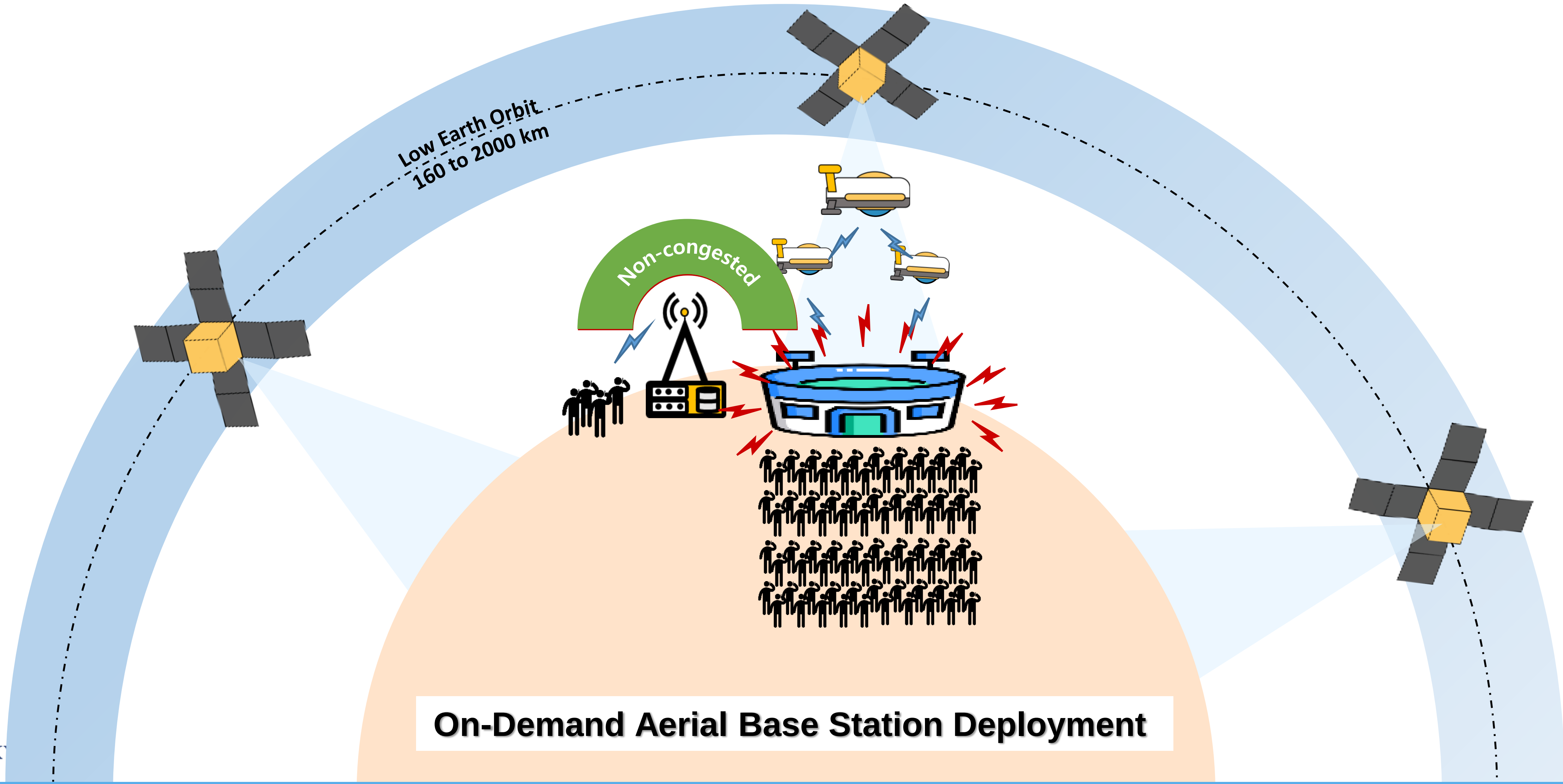
https://dronelife.com/2019/03/11/droneii-tech-talk-unraveling-5-levels-of-drone-autonomy/

Industrial Applications: Examples



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

Industrial Applications: Temporary Events



On-Demand Aerial Base Station Deployment

Industrial Applications: Smart Farming

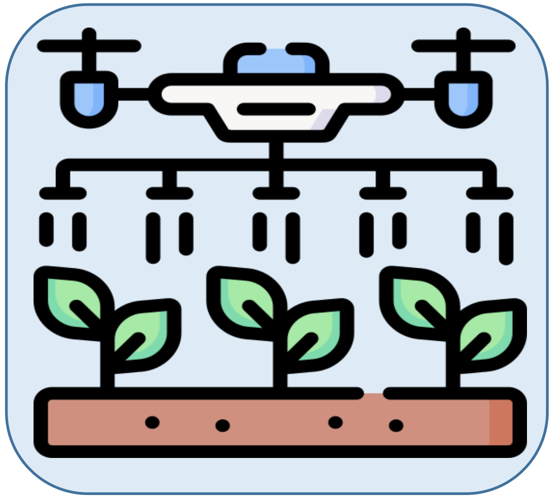
- To access the vegetation health by using Remote Sensing (RS) techniques and image analytics.

- 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 are drones are characterized as a more economical solution

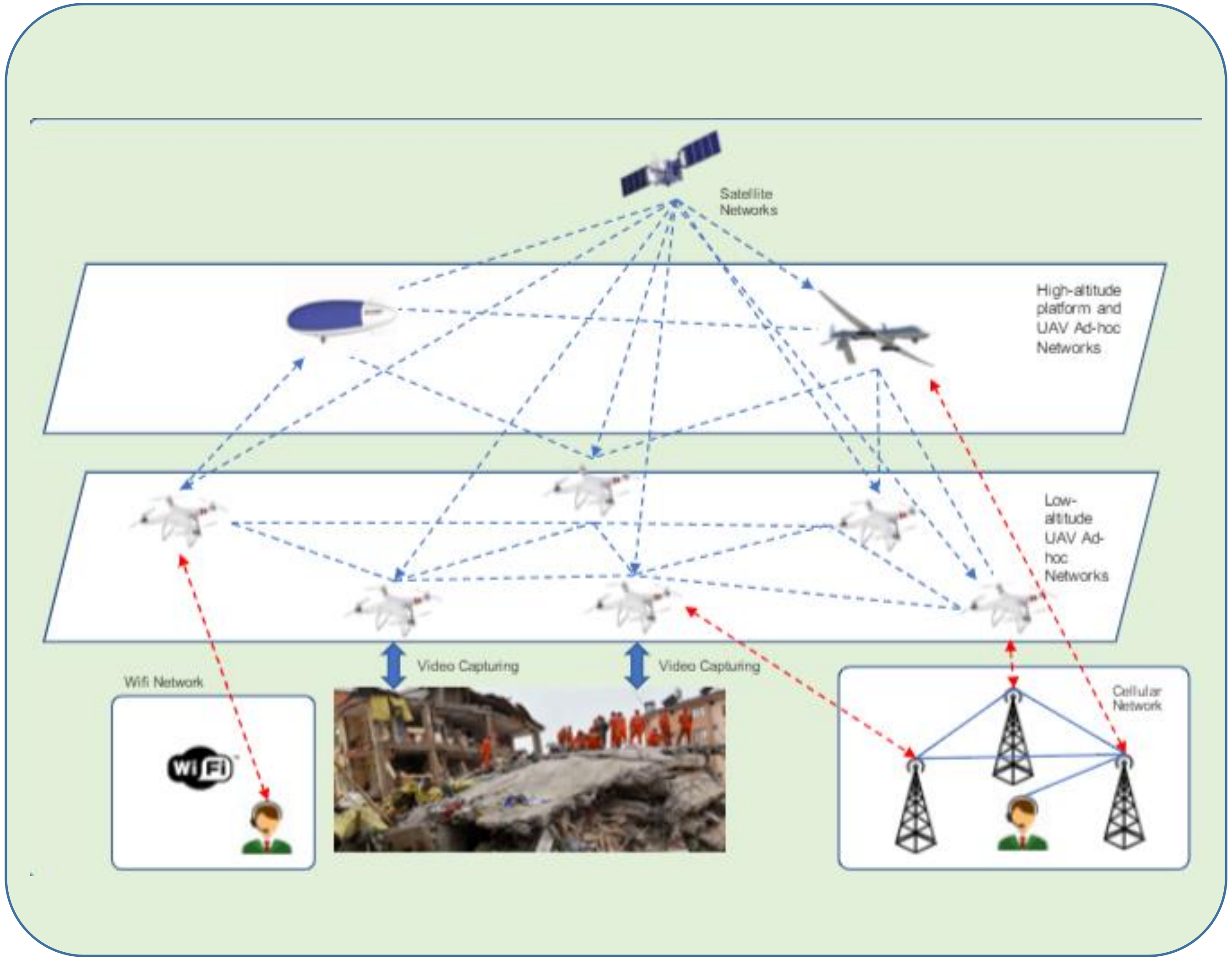


Panagiotis Radoglou-Grammatikis, Panagiotis Sarigiannidis, Thomas Lagka, Ioannis Moscholios, “ A compilation of UAV applications for precision agriculture, Computer Networks, 2020.

Industrial Applications: Disaster Areas

- At the top level, UAVs connect to the GPS satellite by equipping 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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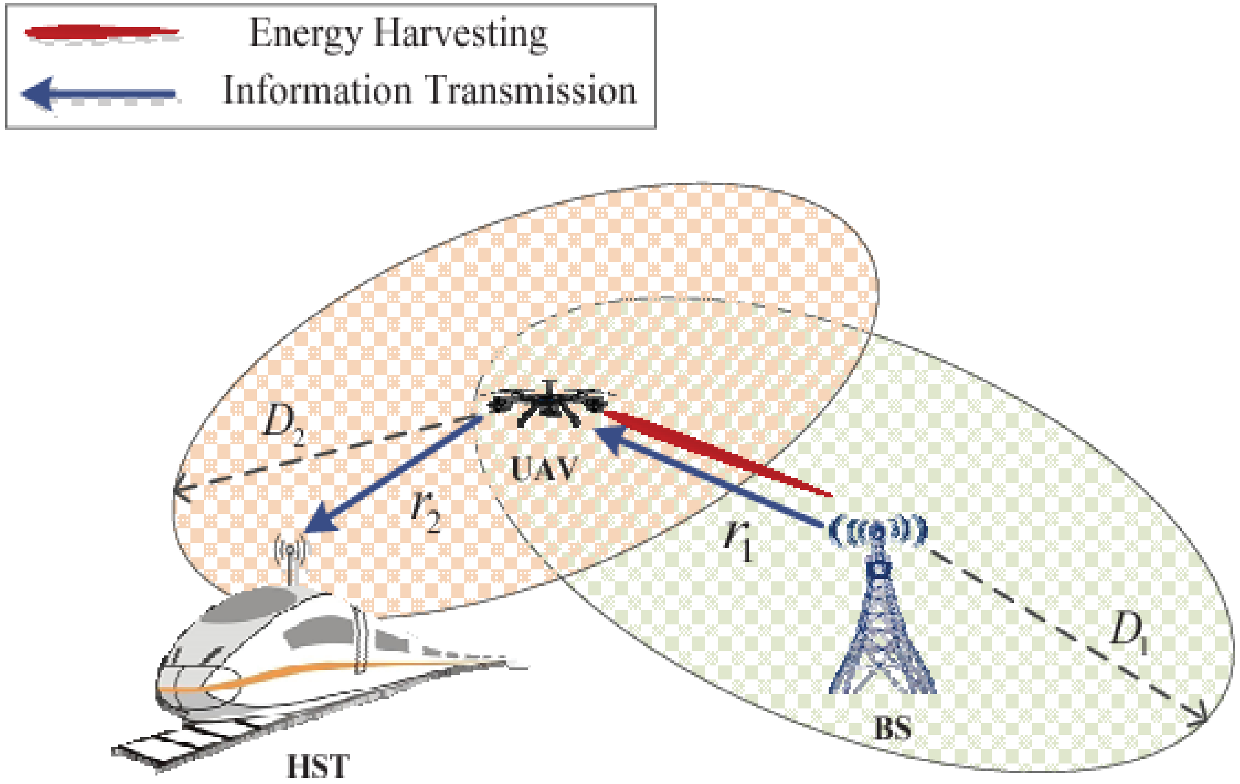
- UAV can also be used as a relay for vehicles and high speed trains



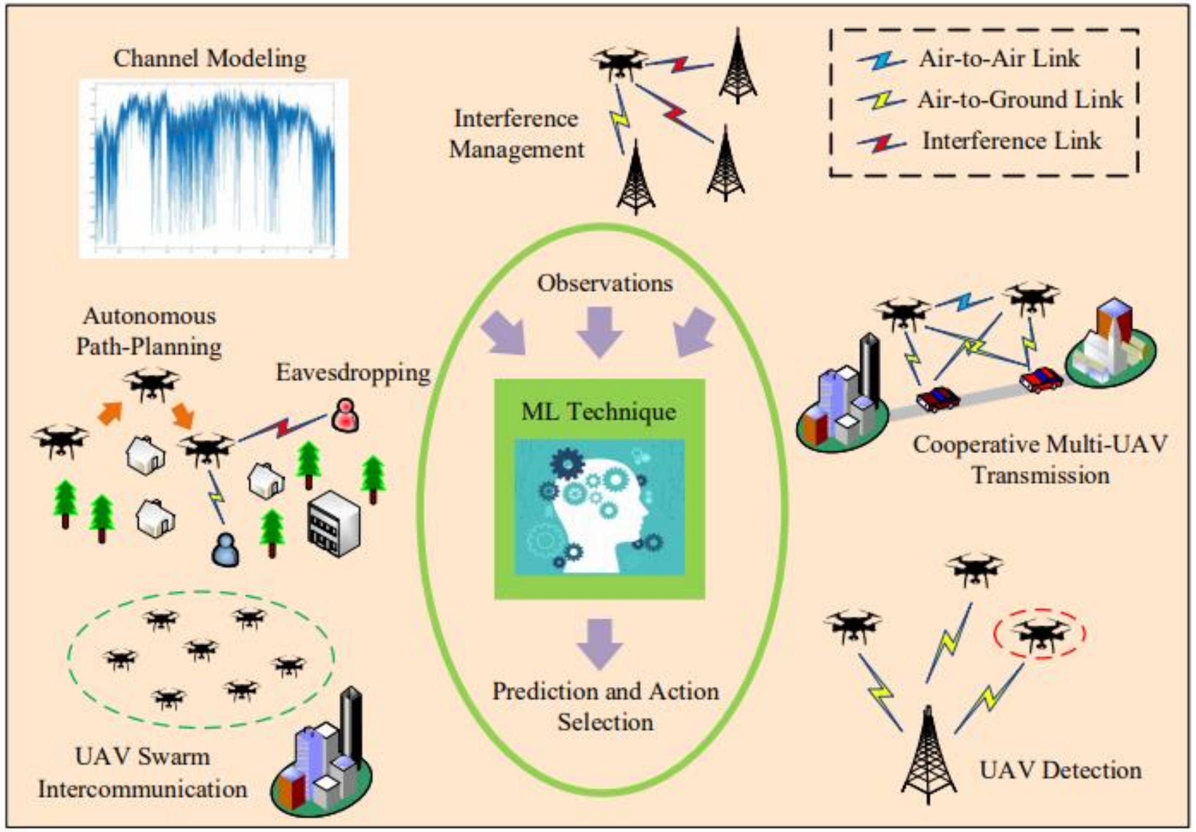
Haitham S. Khallaf, and Murat Uysal, "UAV-Based FSO Communications for High Speed Train Backhauling", IEEE WCNC 2019.

Challenges to deploy UAVs in Communication System

- UAVs are energy constrained devices. Therefore, efficient energy management is essential.
- Energy-aware trajectory optimization for the good channel quality
- Optimal communication and computation resource allocation to overcome the onboard energy limitation while meeting the users' QoS requirements
- The dynamic deployment of 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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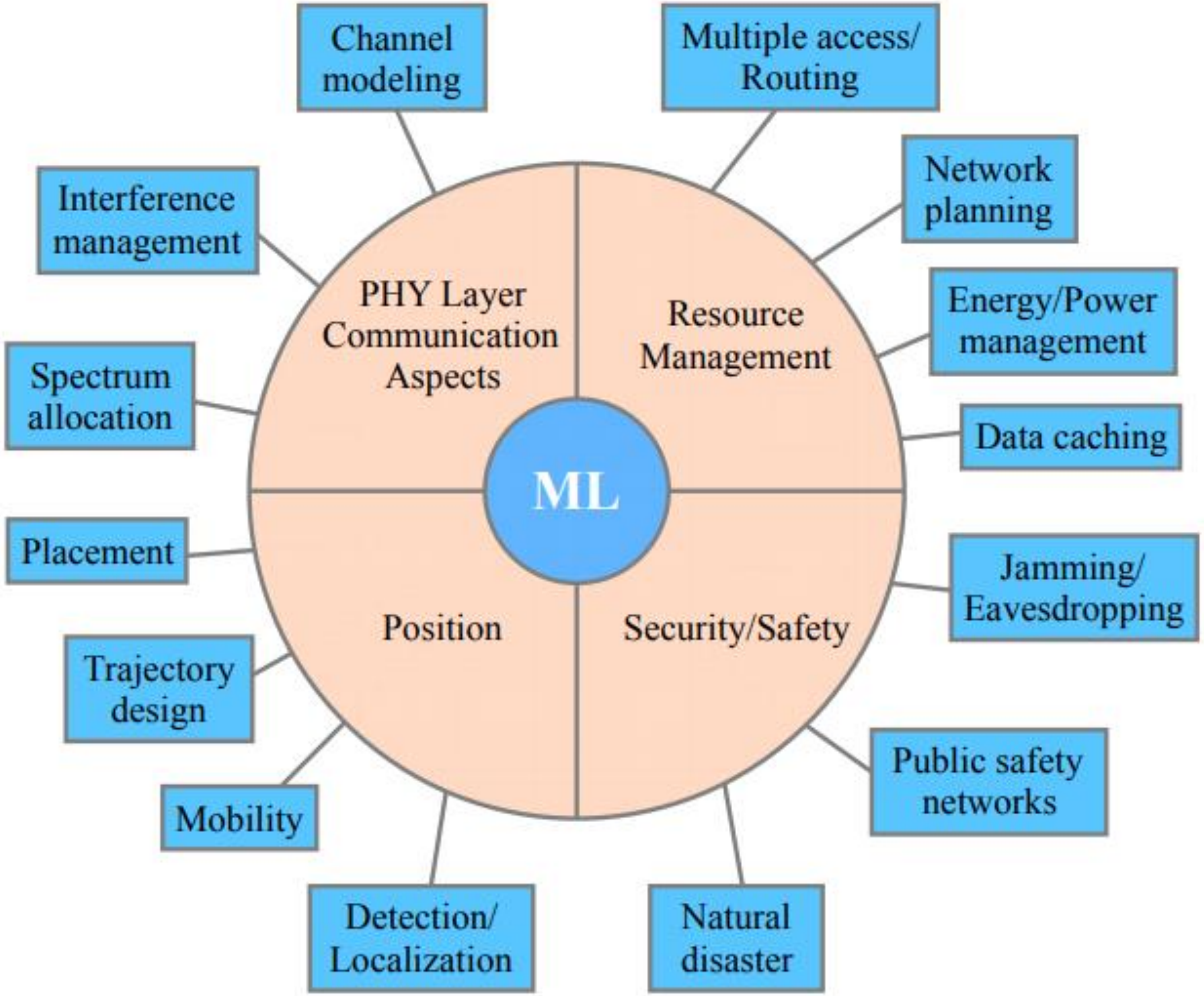
Applications of the AI/ML in UAV-based communications



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

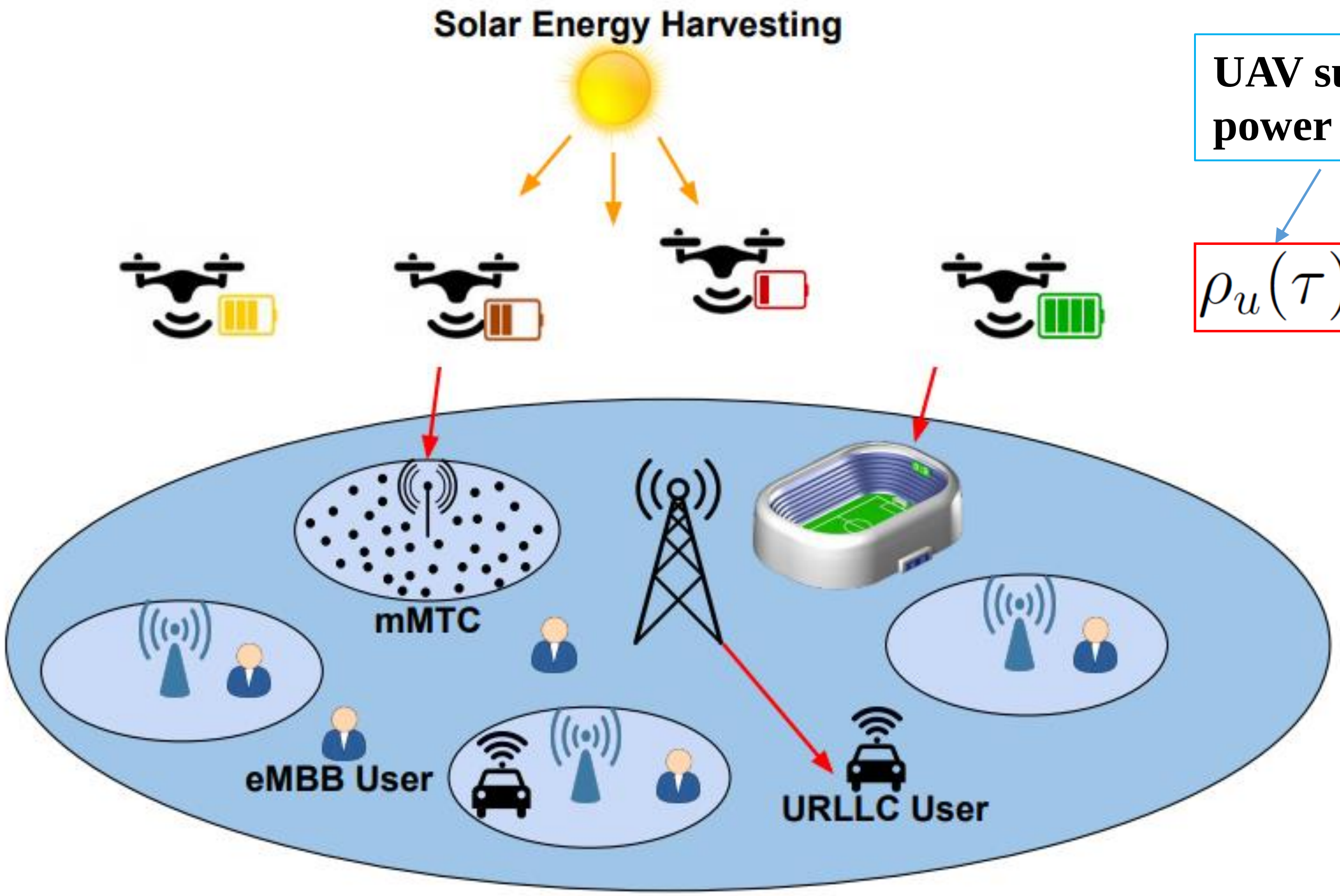
- Introduction
- System Model
- Ruin Theory Preliminaries
- Problem Formulation
- Solution Approach
- Simulation Results

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



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

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

- SINR:

Power

Channel gain

Noise

Interference

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

- Channel gain:

Pathloss

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

- Path-loss:

Los pathloss

LoS losses

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

Non-Los pathloss

Non-Los Losses

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

Total pathloss

Probability of non-Los

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

Environmental constants

- Probability of LoS:

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

- Data rate:

Association

Bandwidth

SNR

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

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Aunas Manzoor, C. S. Hong et al. "Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks". IEEE Transactions on Communications, Vol. 69, No.6 pp. 3943-3954, June 2021

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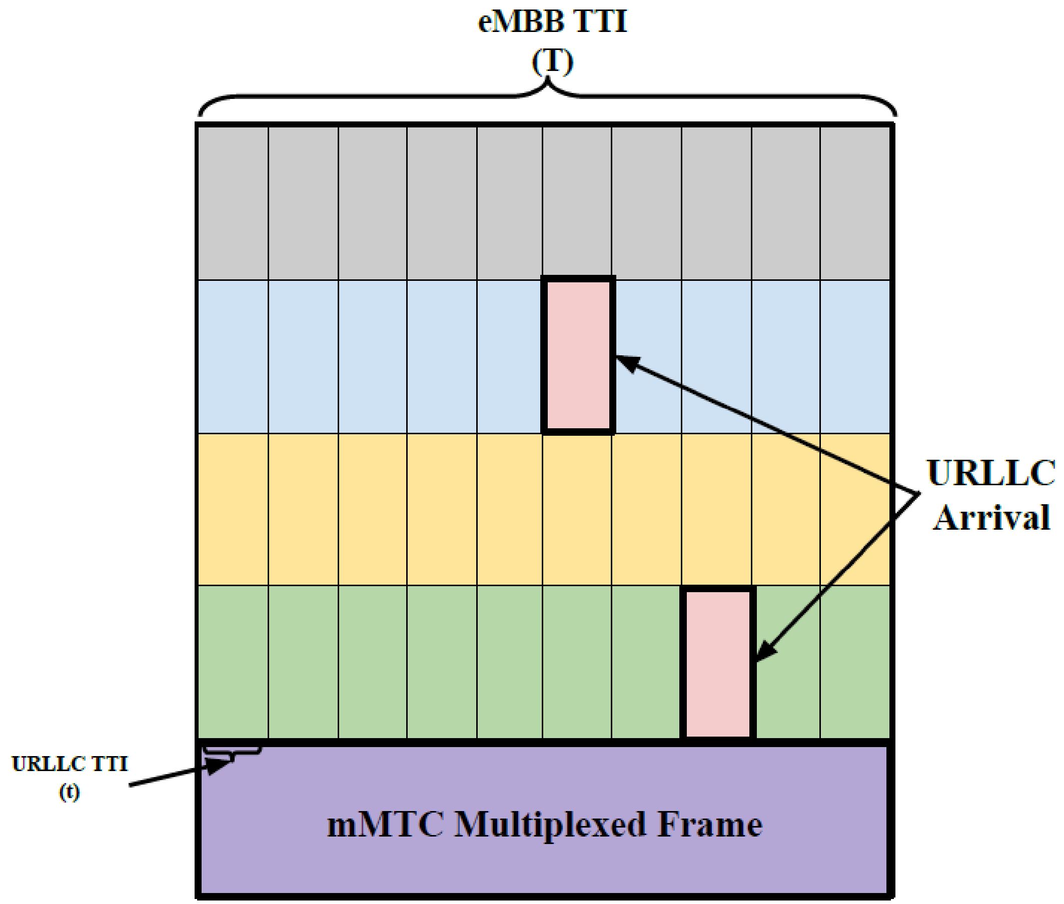
5G-NR coexistence frame structure



Djk represents the amount of data which can be communicated from BS j to the eMBB user k during time T

$$D_{jk}\left(x_{jk}, P_{jk}\right) = \left(T - t \sum_{k' \in \mathcal{K}_u} \overbrace{\boxed{x_{jk'}}}^{\text{URLLC Association}}\right) \overbrace{\boxed{R_{jk},}}^{\text{eMBB Rate}} \quad \forall k \in \mathcal{K}_e,$$

TTI: Transmission Time Interval

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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

$$\rho_u(\tau) = \underbrace{\boxed{\rho_0}}_{\text{Initial power}} + \underbrace{\boxed{\rho\tau}}_{\text{Premium (harvesting power)}} - \underbrace{\boxed{S_u}}_{\text{Random claims (power cosumed by transmitting)}}$$

- 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". IEEE Transactions on Communications, Vol. 69, No.6 pp. 3943-3954, June 2021

Total transmission and processing cost minimization problem.

Data rate

Probability of ruin

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

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

BS transmission power budget

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

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

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

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

Variable bounds

Aunas Manzoor, C. S. Hong et al. "Ruin Theory for Energy-Efficient Resource Allocation in UAV-assisted Cellular Networks". IEEE Transactions on Communications, Vol. 69, No.6 pp. 3943-3954, June 2021

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

$\Pr(\gamma_{jk'} \geq \zeta)$ 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 $\gamma_{jk'} = \zeta$

the inverse CDF of γjk ,

- Compute optimal power

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

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

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

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eMBB User Association

- Association problem:

The finite-time probability of ruin

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

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

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

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

Control factor

Algorithm 1 User Association Algorithm

Input: J, K, P_{jk}, ρ_j
initialize: $x^*_{jk} = 0$
Step 1:
Compute $\psi_u(\rho_0, t)$ from (10)
Compute η_{jk} from (16)
for $k = 1$ **to** K **do**
  Select single BS j with $\max_{j \in \mathcal{J}} \eta_{jk}$
end for
Step 2:
for $j = 1$ **to** J **do**
  Initialize $P = \rho_j$
  while $P \geq 0$ **do**
    Find $\max_{k \in \mathcal{K}} \gamma_{jk}$
    Update $x^*_{jk} = 1$, and $P = P - P_{jk}$
    Remove $\max_{k \in \mathcal{K}} \gamma_{jk}$ from $SINR$ vector γ_{jk}
  end while
end for

The achievable rate for the set of the associated eMBB users

- Power Allocation Problem:

$$\max_{\boldsymbol{P}} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}_e} R'_{jk},$$

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

$$0 \leq p_{jk} \leq p_{\max}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_e.$$

- Standard Form of Power Allocation Problem:

$$\min_{\boldsymbol{P}} \quad -\sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}_e} x^*_{jk} \omega_{jk} \log\left(1 + \gamma_{jk}\right),$$

$$\text{s.t.} \sum_{k \in \mathcal{K}_e} P_{jk} = \rho_j - \sum_{k' \in \mathcal{K}_u} P^*_{jk'}, \quad \forall j \in \mathcal{J},$$

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

$$P_{jk} \leq p_{\max}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_e.$$

eMBB Power Allocation

When the KKT conditions are satisfied, the optimal solution of the Lagrangian function is obtained

- Lagrangian Function:

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

- KKT Conditions

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

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

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

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

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

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

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

θjk is the channel gain for the user k from BS j

Lagrangian multiplier for power budget constraint of BS

- Optimal Power

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

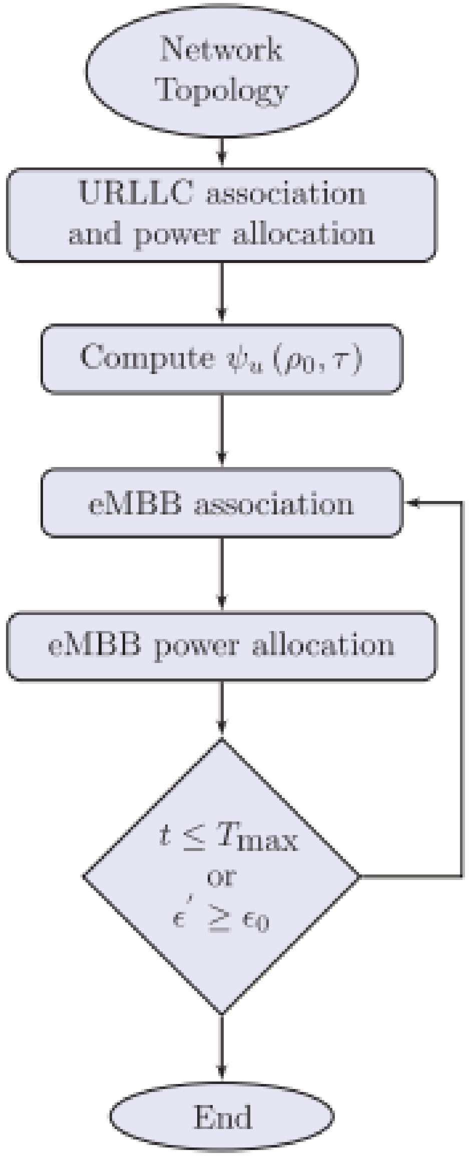
eMBB Power Allocation

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

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

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

Systematic Diagram of Proposed Algorithm



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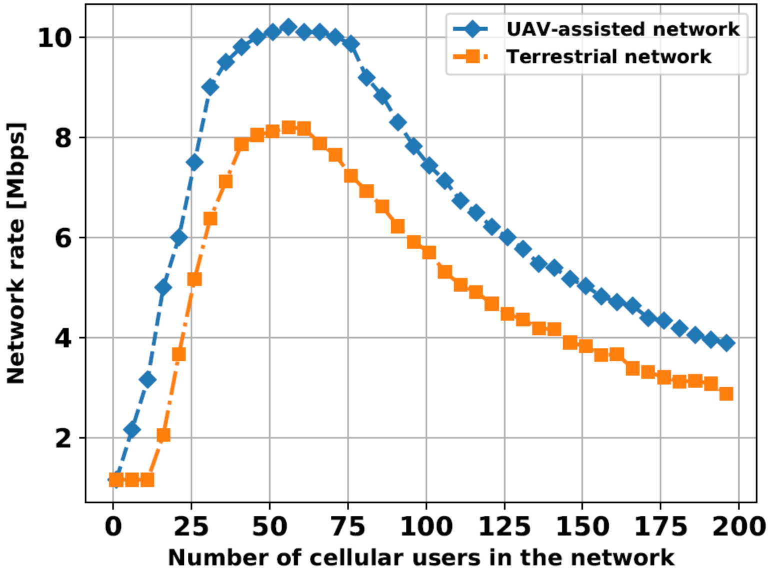
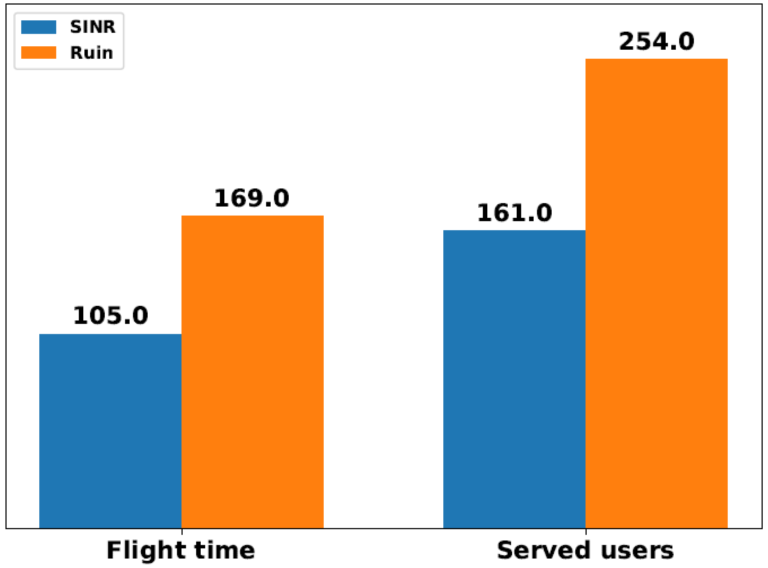
Performance Evaluation (1)



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.

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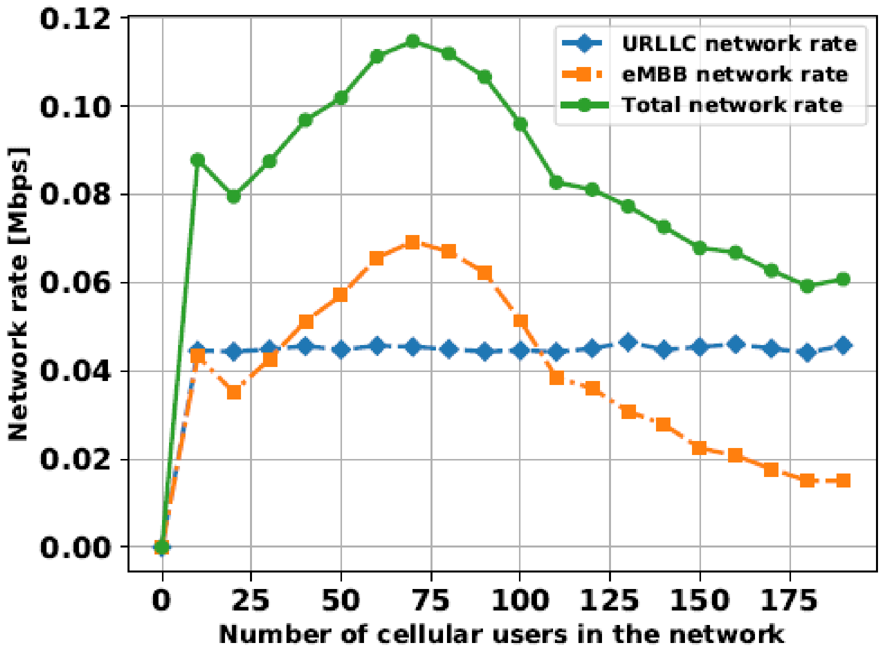
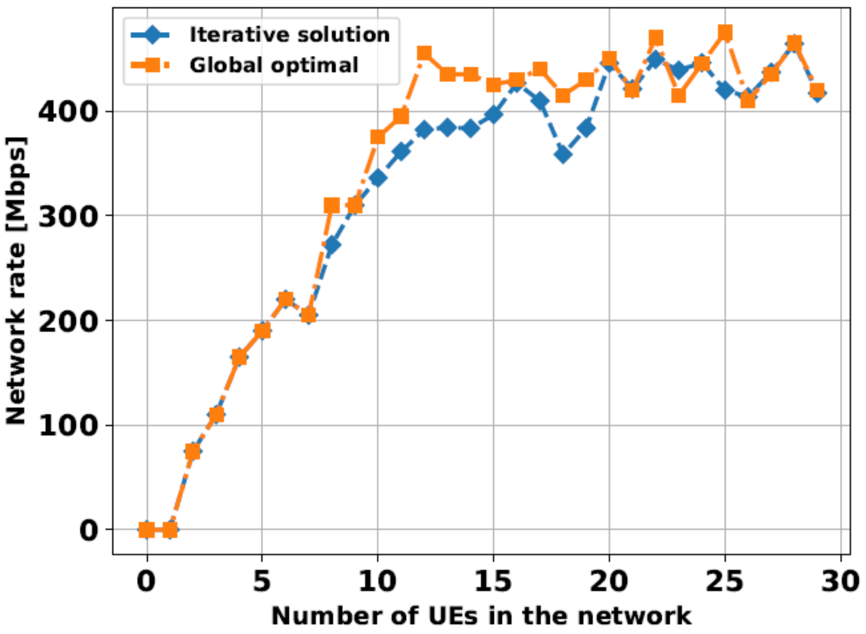
Performance Evaluation (2)





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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.

S.M. Ahsan Kazmi, Latif U. Khan, Nguyen H. Tran, Choong Seon Hong, "Network Slicing for 5G and Beyond Networks," ISBN 978-3-030-16169-9, Springer

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

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

Introduction

- 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

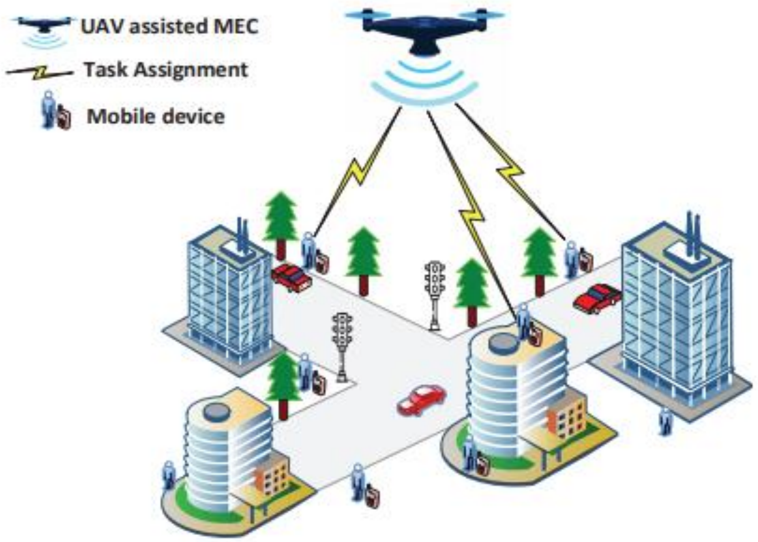

Fig. 1: Illustration of our system model.

- 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 : $\mathbf{c}(1) = \mathbf{c}(N)$

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Communication Model

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

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

the length of each time slot

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

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

$$k = 0.5M$$

UAV weight

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

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

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

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

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':

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

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

A constant which depends on the chip architecture of the mobile device

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’:

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

- The uplink energy consumption:

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

- The computation latency at UAV:

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

Computation capacity of UAV allocated to device ‘n’

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

$$E_u^{\text{exe}}(n) = q(f_u^C)^2 \beta_u l_u(n), \quad \forall n \in \mathcal{N},$$

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

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:

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

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

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

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

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

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

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

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

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

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

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

- The proximal upper-bound function:

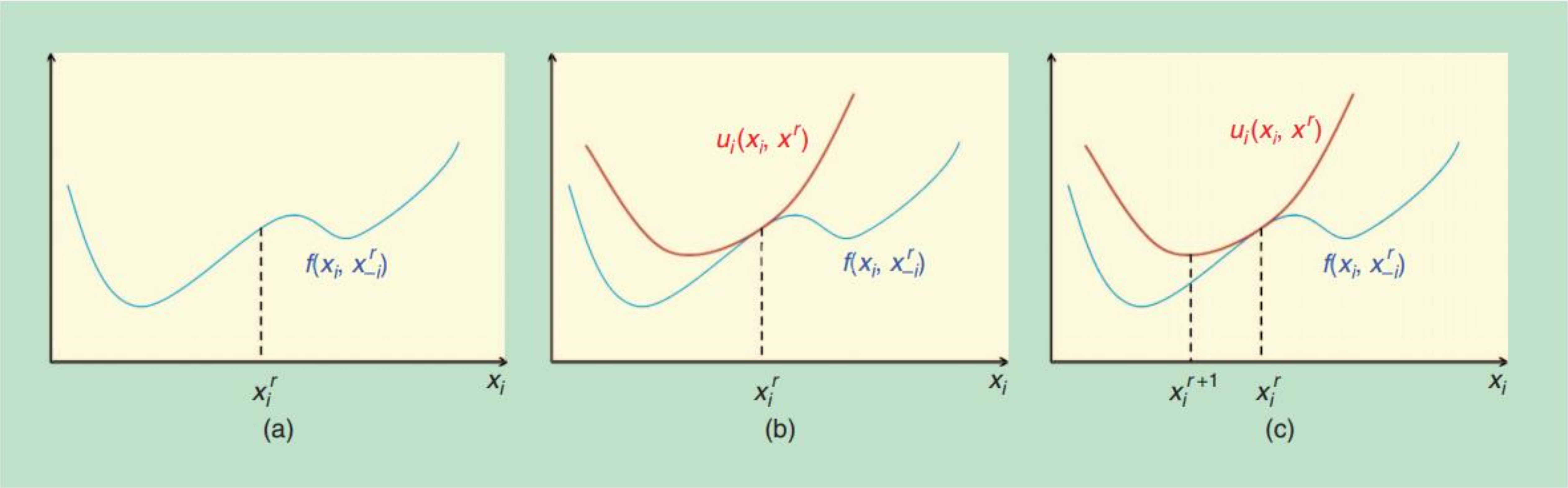
$$\mathcal{O}_i(\boldsymbol{c}_i; \boldsymbol{c}^k, \boldsymbol{l}^k, \boldsymbol{\alpha}^k, \boldsymbol{p}^k, \boldsymbol{f}^k) = \mathcal{O}(\boldsymbol{c}_i; \tilde{\boldsymbol{c}}, \tilde{\boldsymbol{l}}, \tilde{\boldsymbol{\alpha}}, \tilde{\boldsymbol{p}}, \tilde{\boldsymbol{f}}) + \frac{\mu_i}{2} \parallel (\boldsymbol{c}_i - \tilde{\boldsymbol{c}}) \parallel^2,$$

Penalty term

MINLP: Mixed Integer NonLinear Programming

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.

Block Successive Upper-bound Minimization (BSUM)



[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.

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.

Solution Approach

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

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

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

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

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

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

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

1: **Initialization:** Set $k = 0$, $\epsilon_1 > 0$, and find initial feasible solutions $(\boldsymbol{c}^{(0)}, \boldsymbol{l}^{(0)}, \boldsymbol{\alpha}^{(0)}, \boldsymbol{p}^{(0)}, \boldsymbol{f}^{(0)})$;
2: **repeat**
3: Choose index set $\mathcal{I}^k$;
4: Let $\boldsymbol{c}_i^{(k+1)} \in \min_{\boldsymbol{c}_i \in \mathcal{C}} \mathcal{O}_i(\boldsymbol{c}_i; \boldsymbol{c}^{(k)}, \boldsymbol{l}^{(k)}, \boldsymbol{\alpha}^{(k)}, \boldsymbol{p}^{(k)}, \boldsymbol{f}^{(k)})$;
5: Set $\boldsymbol{c}_j^{(k+1)} = \boldsymbol{c}_j^k, \forall j \notin \mathcal{I}^k$;
6: 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);
7: $k = k + 1$;
8: **until** $\left\| \frac{\mathcal{O}_i^{(k)} - \mathcal{O}_i^{(k+1)}}{\mathcal{O}_i^{(k)}} \right\| \leq \epsilon_1$
9: 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

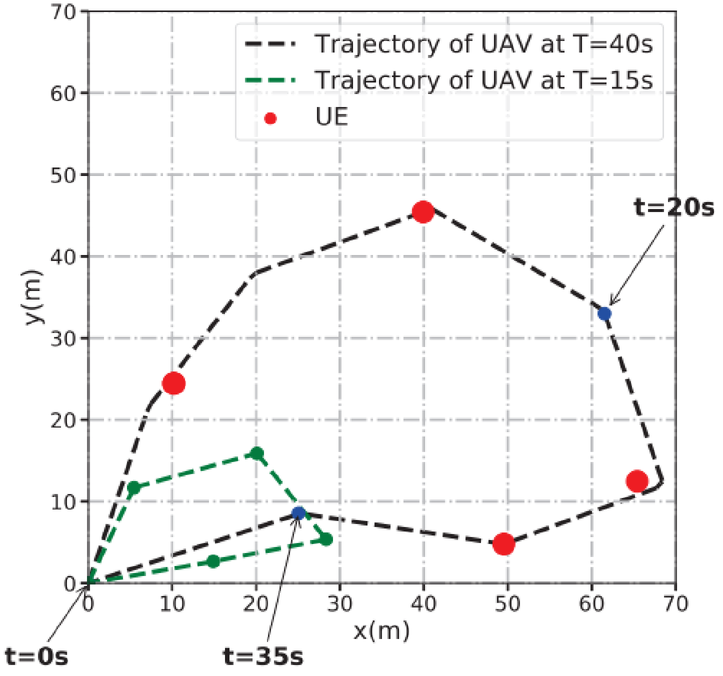
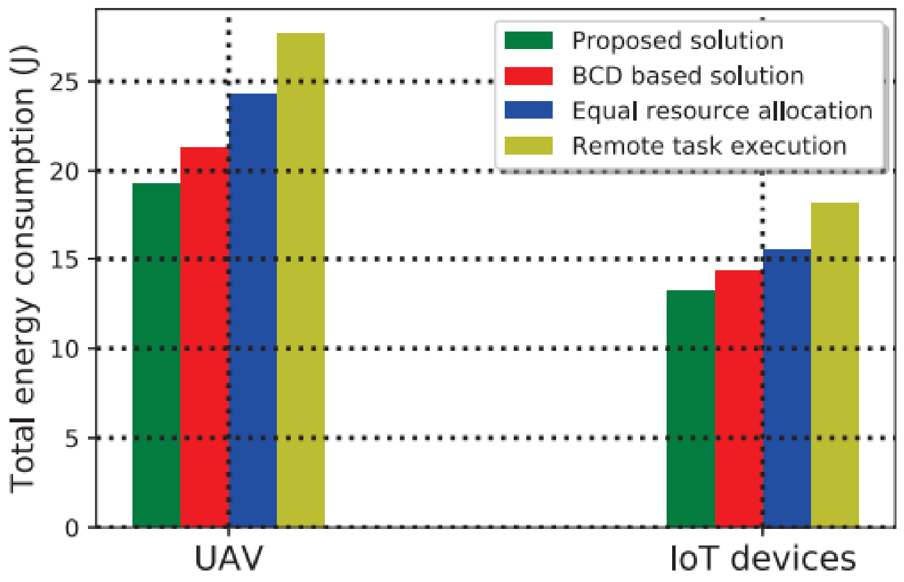


Fig. 2: Trajectories of UAV under different flight period T.



(a)

*BCD: Block Coordinate Descent

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

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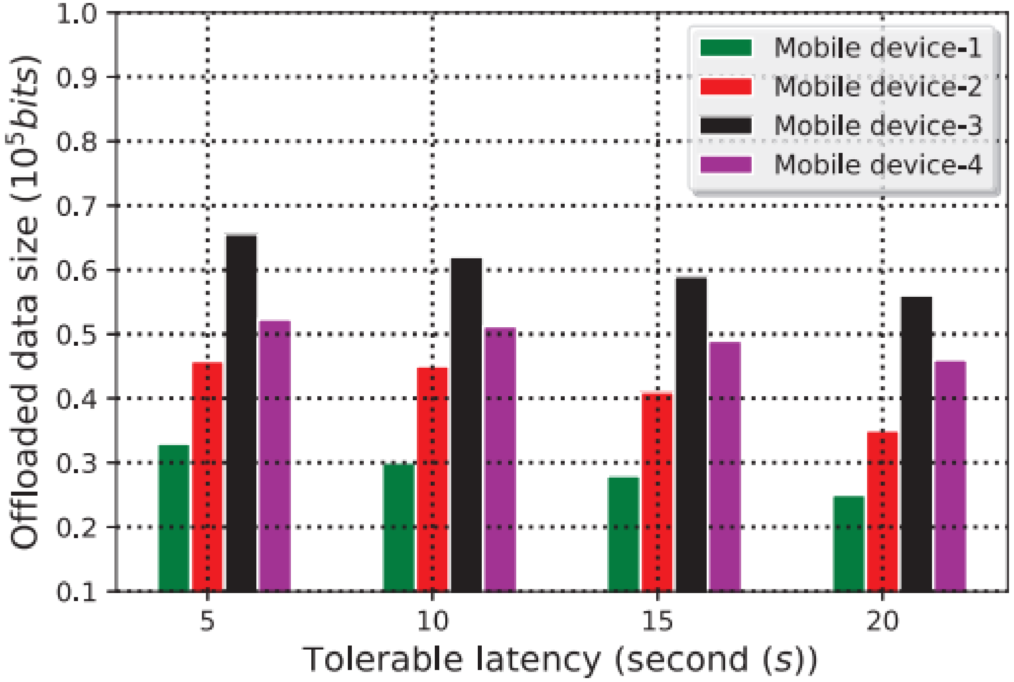


(c)

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

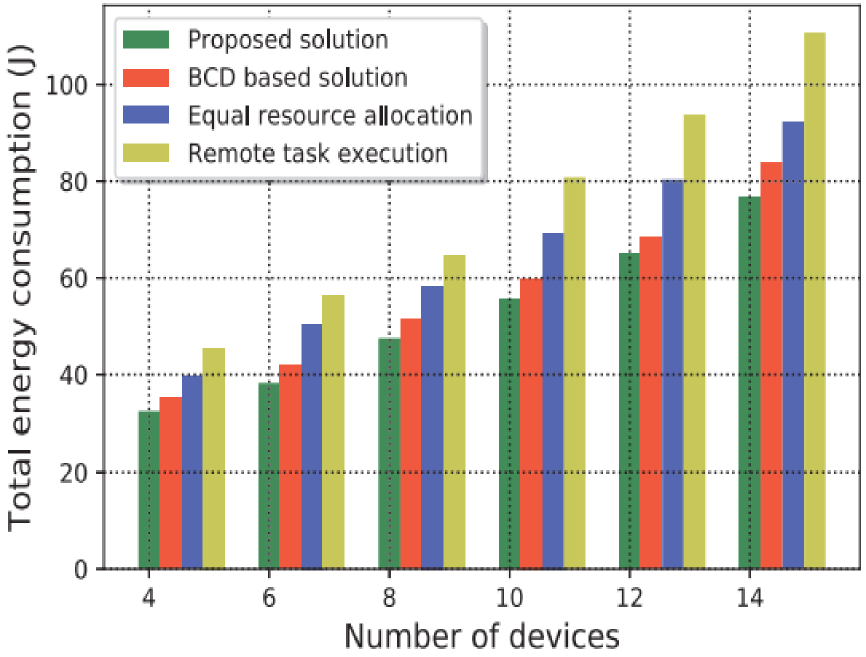


Fig. 4: Energy consumption under different number of mobile devices.

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.

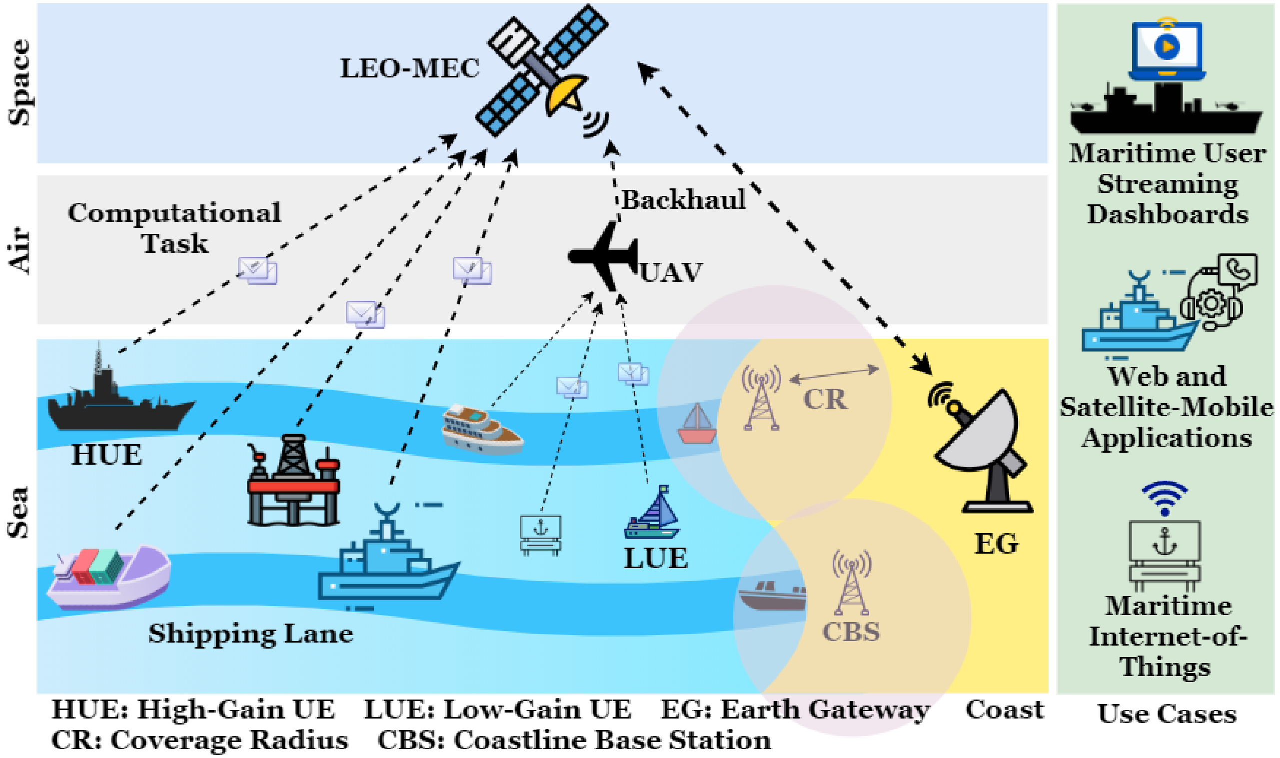
Yan Kyaw Tun, Yu Min Park, Nguyen H.Tran, Walid Saad, Shashi Raj Pandey, and Choong Seon Hong, "Energy-Efficient Resource Management in UAV-Assisted Mobile Edge Computing", IEEE Communication Letters, Oct 2020.

Use Case 3: Blue Data Computation Maximization in 6G Space-Air-Sea Non-Terrestrial Networks

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

System model for space-air-sea (SAS) networking

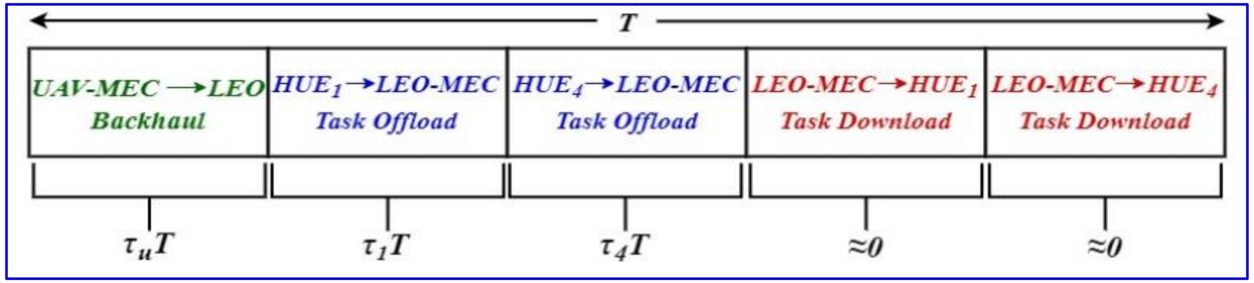
- The seamless and reliable demand for communication is investigated to execute computational tasks in maritime wireless networks
- Proposing an LEO-MEC satellite and UAV-MEC-enabled 6G SAS-NTN architecture by considering both variants of maritime users, i.e., high and low communication capabilities
- The objective is to maximize sum rate of the space-air-sea network (i.e., maritime network)



S. S. Hassan, Y. K. Tun, W. Saad, Z. Han and **C. S. Hong**, "Blue Data Computation Maximization in 6G Space-Air-Sea Non-Terrestrial Networks," 2021 IEEE Global Communications Conference (GLOBECOM), 2021.

Summary of investigation

- Maritime network traffic has grown significantly in recent years due to sea transportation [1].
- Non-terrestrial networks (NTN), encompassing space and air platforms, are a key component of the upcoming sixth-generation (6G) cellular networks.
- A joint task offloading and time allocation problem for weighted sum-rate maximization is formulated as a mixed-integer non-linear programming (MINLP).
- A solution based on the Bender and primal decomposition is proposed.



Example of LEO-MEC time resource allocation

S. S. Hassan, Y. K. Tun, W. Saad, Z. Han and **C. S. Hong**, "Blue Data Computation Maximization in 6G Space-Air-Sea Non-Terrestrial Networks," 2021 IEEE Global Communications Conference (GLOBECOM), 2021.
[1] Source: https://www.marketsandmarkets.com/Market-Reports/maritime-satellite-communication-market-113822978.html

- The weighted communication sum rate of the space-air-sea network (i.e., maritime network)

$$R(\boldsymbol{g}, \boldsymbol{y}, \boldsymbol{\tau}_i, \tau_u) \triangleq \sum_{i=1}^{M_h} z_i \left((1 - y_i) R_i^{\text{Local}} + y_i R_i^{\text{LEO}} \right) + R^{\text{UAV}}, \quad (7)$$

Weight Parameter for HUE *i depends upon their channel condition*

Offloading decision variable, decide whether compute locally or transmit to LEO-MEC

- The objective is to maximize the weighted sum rate for the considered space-air-sea network
- The formulated mixed-integer non-linear optimization problem is as follows:

Channel Gain Input

Decision variables that need to optimize

$$R^*(\boldsymbol{g}) = \max_{\boldsymbol{y}, \tau_u, \boldsymbol{\tau}_i} \quad R(\boxed{\boldsymbol{g}}, \underbrace{\boldsymbol{y}, \boldsymbol{\tau}_i, \tau_u}), \quad (8a)$$

$$\text{s.t.} \quad \tau_u + \sum_{i=1}^{M_h} \tau_i \leq T, \quad (8b)$$

$$\tau_u > 0, \tau_i \geq 0, \quad \forall i \in \mathcal{M}_h, \quad (8c)$$

$$y_i \in \{0, 1\}, \quad \forall i \in \mathcal{M}_h. \quad (8d)$$

Offloading decision

Time duration for UAV

Time duration for HUE

Total time duration constraint

Each allocated time duration should be greater than zero

Whether HUE *i* will transmit its offloading task to the LEO-MEC or compute locally

S. S. Hassan, Y. K. Tun, W. Saad, Z. Han and **C. S. Hong**, "Blue Data Computation Maximization in 6G Space-Air-Sea Non-Terrestrial Networks," 2021 IEEE Global Communications Conference (GLOBECOM), 2021.

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Proposed Algorithms

Bender decomposition is used to solve MINLP by decomposing into sub and master problem

Primal Decomposition algorithm for handling coupling constraint

Convergence Criteria

Algorithm 1 Data Computation Maximization and Task Decisions by Bender Decomposition

Minimum objective value (data rate)

Initialize: loop counter $j = 1$, Ψ^{down}, ϵ,
while $R^j_{\text{UB}} - R^j_{\text{LB}} > \epsilon$ **do**
    Subproblem
        Compute optimal τ^{*j}_u, $\boldsymbol{\tau}^{*j}_i$, and κ^j_i by Algorithm 2
    Convergence Analysis
        Compute the lower (R^j_{LB}) and upper (R^j_{UB}) bounds by (10) and (11)
    Master Problem
        Step 1: Update the loop counter $j = j + 1$
        Step 2: Add new cut to the Master problem (13)
        Step 3: Solve the updated master problem
        Step 4: Compute the optimal value of $\boldsymbol{y}^{*j}_i$ and Ψ^j
end while

Fixed offloading decision (dual values)

Upper Bound $R^j_{\text{UB}} = R(\tilde{\boldsymbol{y}}^j, \tau^j_u, \boldsymbol{\tau}^j_i)$.

Optimal offloading decision

Data rate objective value in Master Problem (with lower bound R^i_{LB})

Algorithm 2 Optimal-Time Resource Allocation by Primal Decomposition

Initialize: θ
repeat
    Solve the primal-subproblems in parallel
        Solve problem (17) and acquire the optimal time-resource allocation $\boldsymbol{\tau}^*_i$ for associated HUEs and dual variable associated with constraint (17c).
        Solve problem (18) and acquire the optimal time-resource allocation τ^*_u for UAV-MEC and dual variable associated with constraint (18c).
    Update the time resource allocation auxiliary variable: $\theta = \theta - \zeta(\lambda_2 - \lambda_1)$.
until convergence

After convergence, optimal time values are obtained

S. S. Hassan, Y. K. Tun, W. Saad, Z. Han and **C. S. Hong**, "Blue Data Computation Maximization in 6G Space-Air-Sea Non-Terrestrial Networks," 2021 IEEE Global Communications Conference (GLOBECOM), 2021.

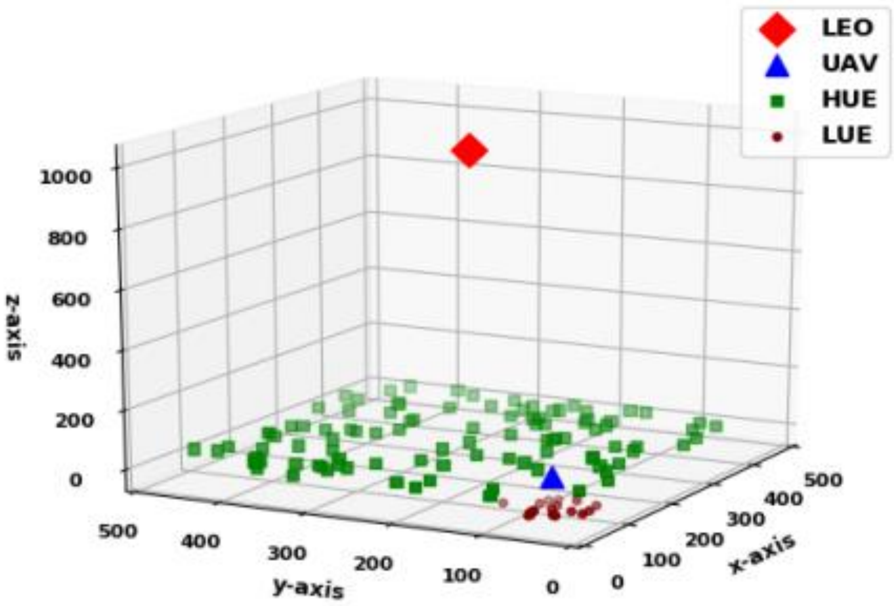
* mixed-integer non-linear programming (MINLP)

✓ Simulation Parameters and Network topology consisting of LEO, UAV, HUEs and LUEs

Simulation Parameters

Parameters	Values
Transmit Power	P = 33 dBm
Noise Power	σ^2 = − 104 dB
Carrier Frequency	f = 30 GHz
System Bandwidth	B = 20 MHz
Communication Packet Overhead	μ = 1.1
Processor Cycles for one bit	χ = 100
HUE Antenna Gain	G_i = 25 dBi
UAV Antenna Gain	G_u = 25 dBi
Satellite Antenna Gain	G_s = 30 dBi
Standard deviation	ω = 0.1
reference distance pathloss	$\tilde{\gamma}$ = 46.4
pathloss exponent	γ = 2
Rician fading parameter	β_i, β_u = 1.59

Network topology

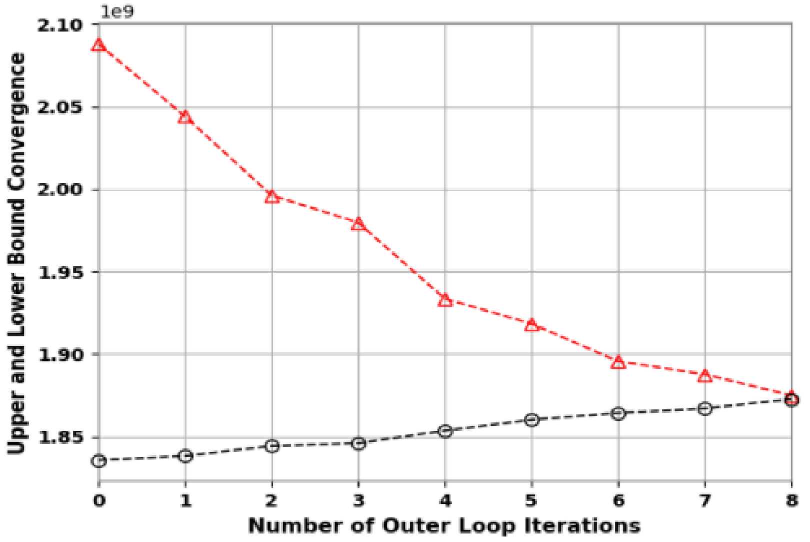


✓ For our simulations, we consider the HUEs in SAS-NTN to be uniformly distributed in 500 nautical mile square area (NM^2)

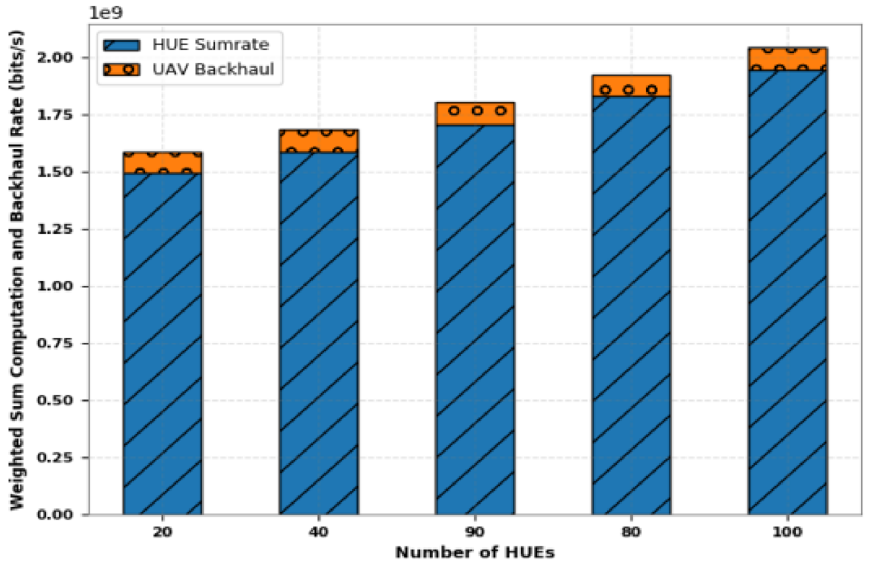
S. S. Hassan, Y. K. Tun, W. Saad, Z. Han and **C. S. Hong**, "Blue Data Computation Maximization in 6G Space-Air-Sea Non-Terrestrial Networks," 2021 IEEE Global Communications Conference (GLOBECOM), 2021.

✓ Experimental Results

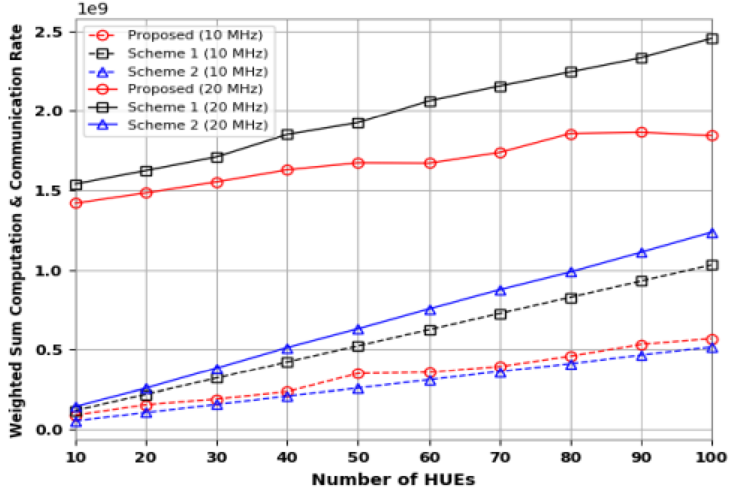
Convergence of Bender decomposition algorithm



Weighted sum-rate (bits/s) vs HUEs



Comparison of proposed algorithm with other schemes



- ✓ Scheme 1: This scheme is considered as optimal results, which are computed by use of a standard optimization solver.
- ✓ Scheme 2: This scheme is regarded as a random task decision and time allocation to each HUE.

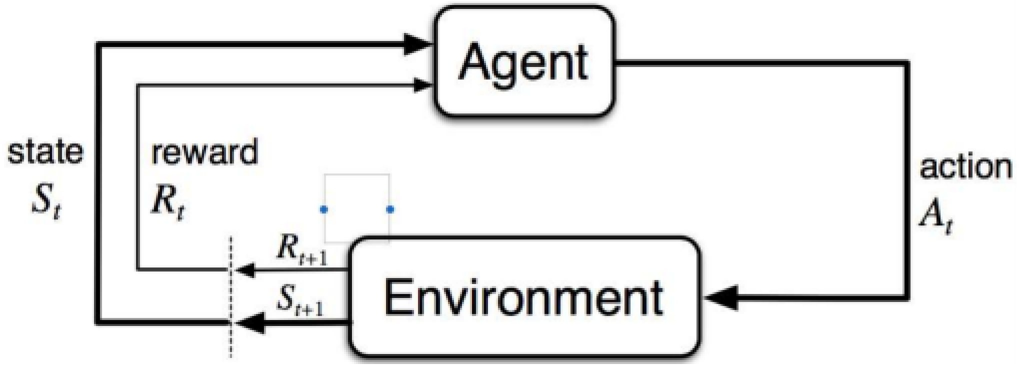
S. S. Hassan, Y. K. Tun, W. Saad, Z. Han and **C. S. Hong**, "Blue Data Computation Maximization in 6G Space-Air-Sea Non-Terrestrial Networks," 2021 IEEE Global Communications Conference (GLOBECOM), 2021.

What is Missing till now?

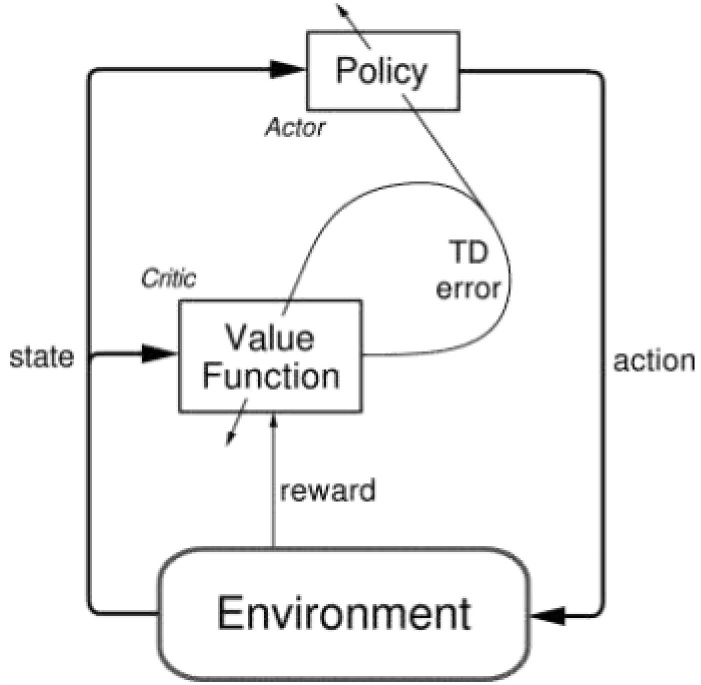
Yes, It is "AI"

Various Machine Learning Approaches

- 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 4: Data Freshness and Energy-Efficient UAV Navigation Optimization: A Deep Reinforcement Learning Approach

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

Introduction

- 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.

Sarder Fakhrul Abedin, Md. Shirajum Munir, Nguyen H. Tran, Zhu Han, and Choong Seon Hong, “Data Freshness and Energy-Efficient UAV Navigation Optimization: A Deep Reinforcement Learning Approach”, IEEE Transactions on IntelligentTransportation System, IEEE Transactions on Intelligent Transportation Systems, Vol.22, No.9, pp. 5994-6006, Sep. 2021

System Model

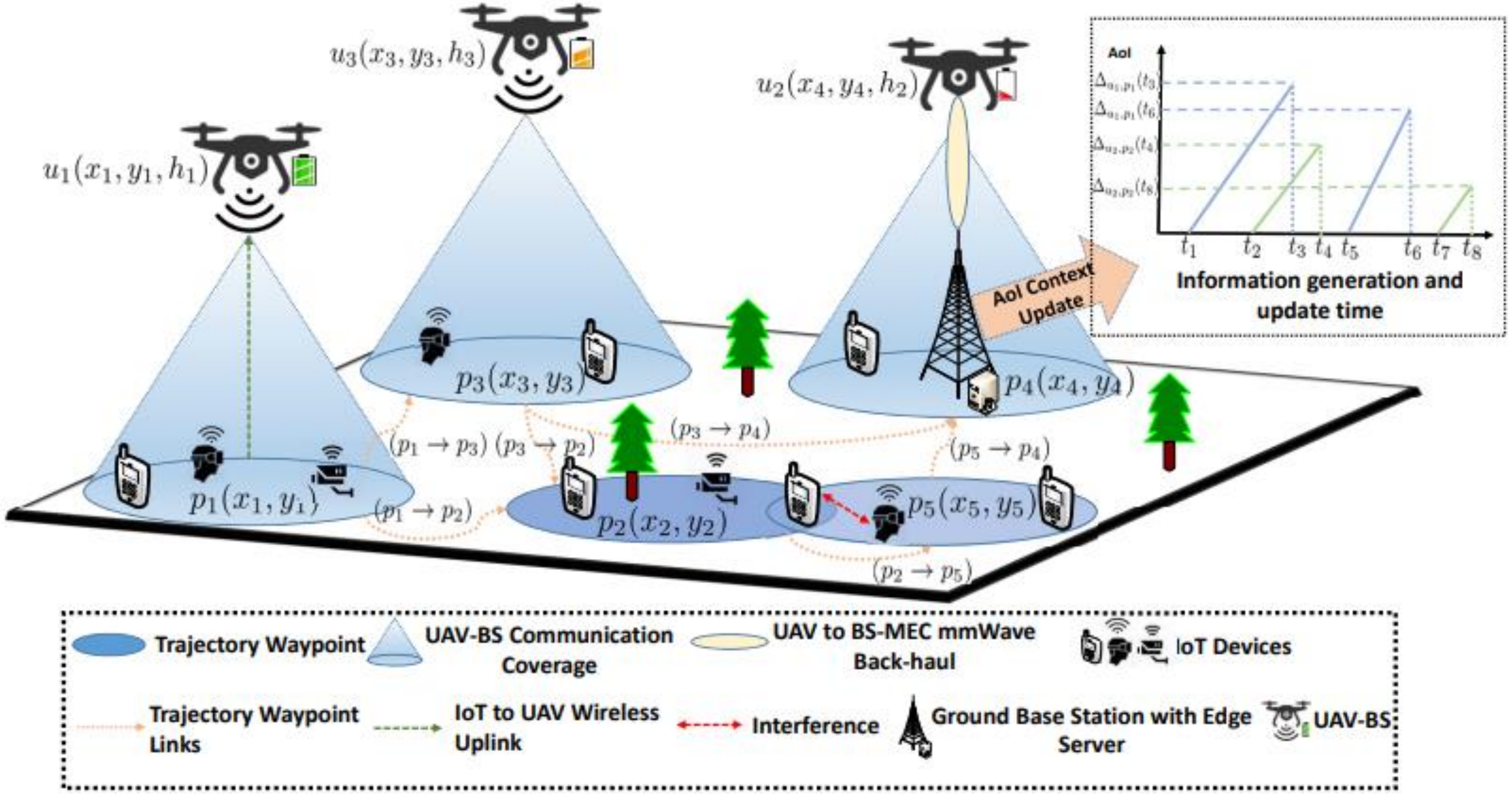


Fig. 1: System Model for Heterogeneous Unmanned Aerial Networks with Edge Computing

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

Sarder Fakhrul Abedin, Md. Shirajum Munir, Nguyen H. Tran, Zhu Han, and Choong Seon Hong, "Data Freshness and Energy-Efficient UAV Navigation Optimization: A Deep Reinforcement Learning Approach", IEEE Transactions on IntelligentTransportation System, IEEE Transactions on Intelligent Transportation Systems, Vol.22, No.9, pp. 5994-6006, Sep. 2021

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

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

Elevation Angle

- Path Loss in decibel (dB):

Distance between UAV and UE

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

Attenuation factors

- Signal to Interference pulse noise ratio

Interference

Received signal power at UAV-BS:

$$\gamma^u_{i,p}(t) = \frac{\hat{P}^u_{i,p}(10^{\frac{\zeta^u_{i,p}}{10}})^{-1}}{I^u_{i,p} + \sigma^2}.$$

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

Channel Model

- Channel capacity at time 't':

Total bandwidth

Total IoT devices

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

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

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

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 :

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

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

Sarder Fakhrul Abedin, Md. Shirajum Munir, Nguyen H. Tran, Zhu Han, and Choong Seon Hong, "Data Freshness and Energy-Efficient UAV Navigation Optimization: A Deep Reinforcement Learning Approach", IEEE Transactions on Intelligent Transportation System, IEEE Transactions on Intelligent Transportation Systems, Vol.22, No.9, pp. 5994-6006, Sep. 2021

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:

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

Problem Formulation

$$\arg\max_{\{\mathcal{P}_u\}_{u\in\mathcal{U}}} \sum_{u\in\mathcal{U}} \eta(\mathcal{P}_u, u), \tag{14}$$

Maximize Energy Efficiency of UAV-BS

subject to

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

Non-Overlapping trajectories of UAV-BSs except ground BS

$$\bigcup_{u\in\mathcal{U}} \mathcal{P}_u = \mathcal{P}, \forall u \in \mathcal{U}, \tag{16}$$

All trajectories points are covered

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

Energy Efficiency constraint

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

AoI constraint

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

- The state space for trajectory:

$$\mathcal{S} = \{s_t = (\underbrace{p^u_{current}}_{\text{Current Positions}}, \underbrace{p_{end}}_{\text{Target Position}}, \overbrace{\eta}^{\text{Energy Efficiency}}, \overbrace{\Delta}^{\text{Average AoI for navigation optimization}}) | \eta \in [0, \eta_{th}], \Delta \in [1, \hat{\Delta}^{th}_b]\}$$

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Solution Approach

- 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:

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

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

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

Discounted cumulated state function

π' ← Control policy

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

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

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

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

Learning rate

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

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Solution Approach

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

Step 1: Initialization
Initialize $Q(s, a; \theta), \mathcal{M}$, target DQN parameters θ^{-} and construct DQN
Step 2: Training DQN with experience replay
for $e = 1, \cdots, E$ **do**
    Initialize $\mathcal{S}$
    for $t = 1, \cdots, T$ **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 $\mathcal{M}$
        Randomly sample minibatch of experiences from $\mathcal{M}$
        Adopt stochastic gradient descent (SGD) to train the DQN using loss function in (27)
        Update θ and $Q(s, a; \theta)$
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 $a_t = \max_{a_t} Q^{\pi^{opt}}(s_t, a; \theta)$
Update trajectory of UAV-BSs based on joint action index and target values of DQN

Building Q- Network

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Numerical Results

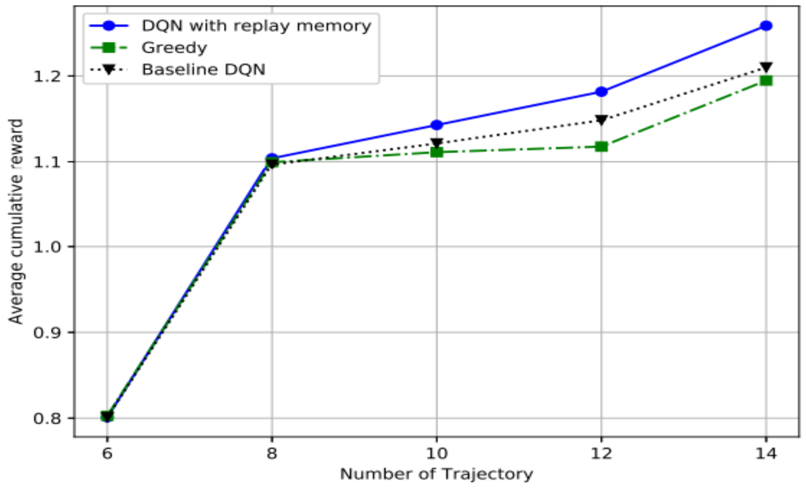

Fig. 2: Average cumulative reward comparison between the proposed approach and the baseline approaches over different numbers of trajectory way-points.

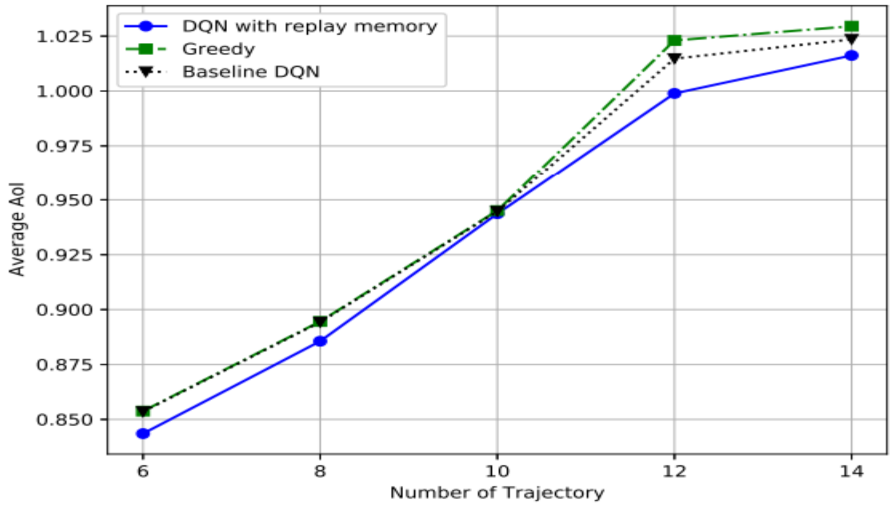

Fig. 3: Average AoI comparison between the proposed approach and the baseline approaches over different number of trajectory way-points.

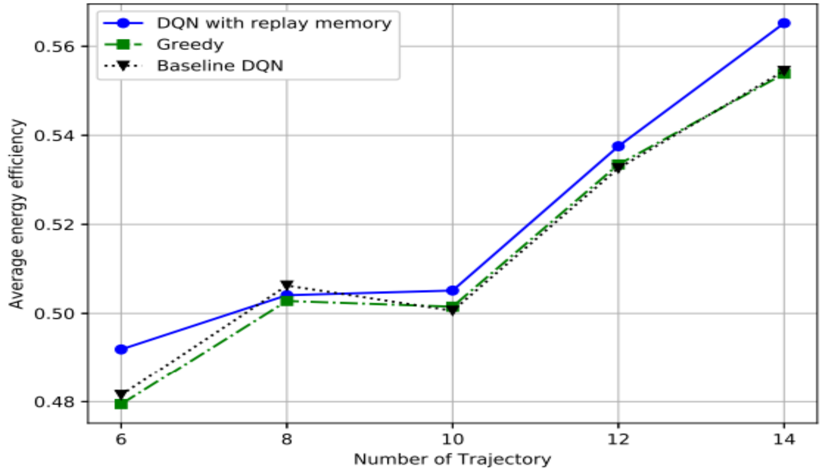

Fig. 4: Average energy efficiency comparison between the proposed and the baseline approaches over different number of trajectory way-points.

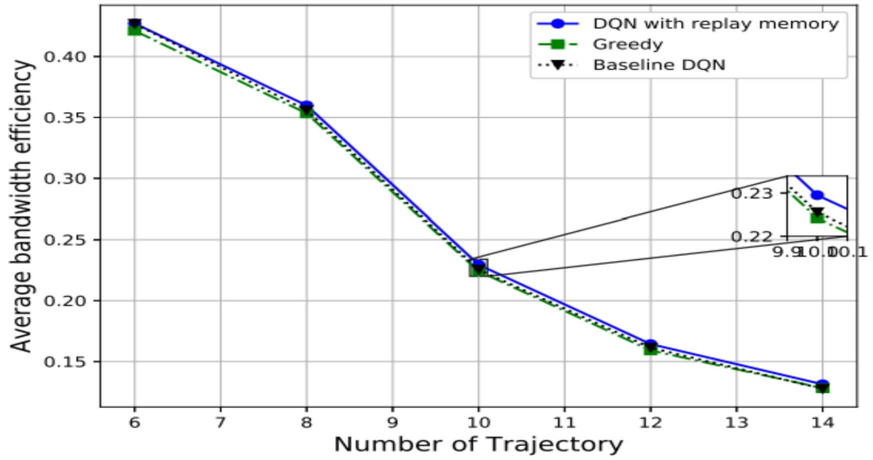

Fig. 5: Average bandwidth efficiency comparison between the proposed and the baseline approaches over different number of trajectory way-points.

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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

Sarder Fakhrul Abedin, Md. Shirajum Munir, Nguyen H. Tran, Zhu Han, and Choong Seon Hong, "Data Freshness and Energy-Efficient UAV Navigation Optimization: A Deep Reinforcement Learning Approach, IEEE Transactions on Intelligence Transportation System, Early Access

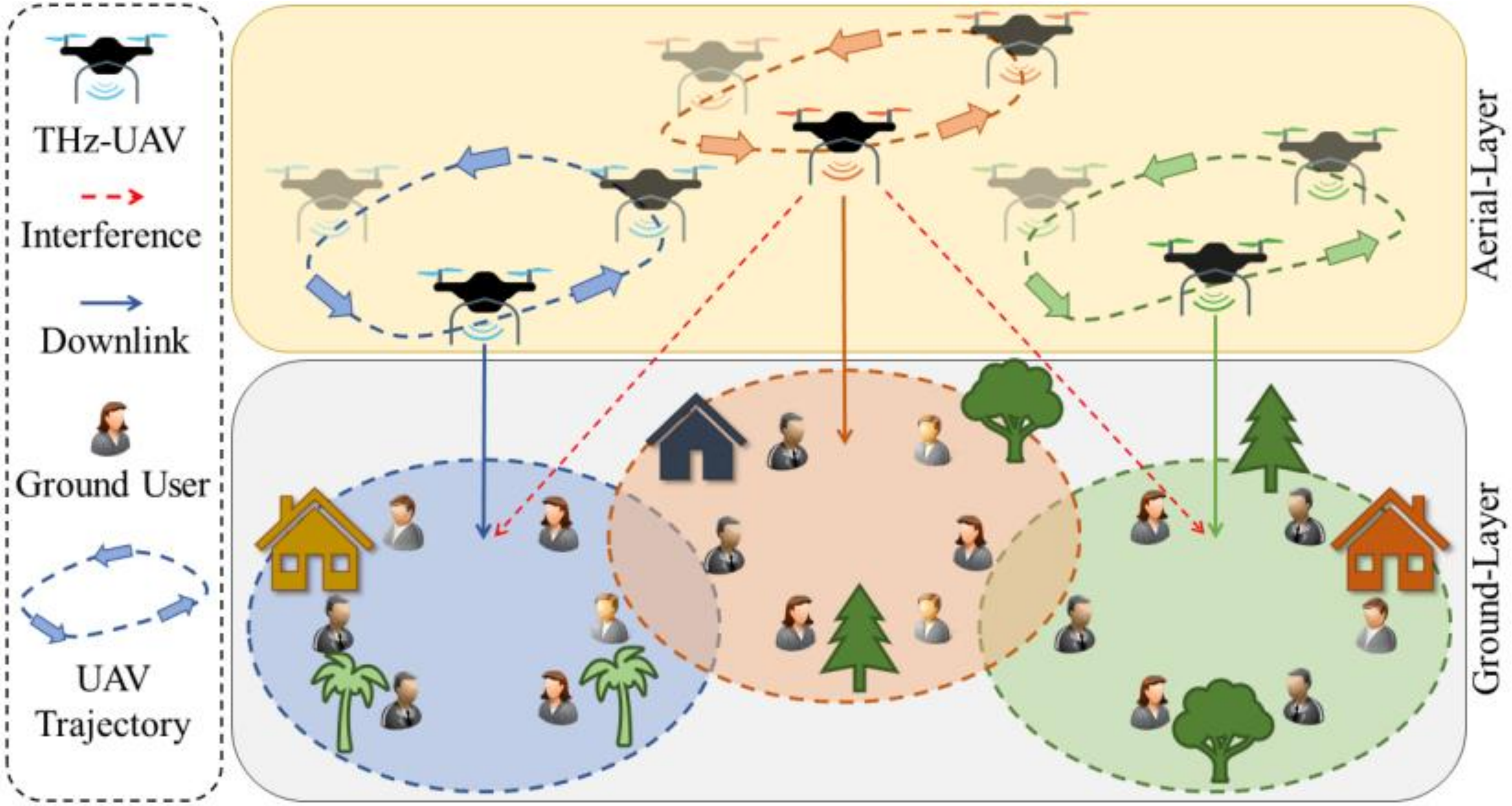
Use Case 5: 3TO: THz-Enabled Throughput and Trajectory Optimization of UAVs in 6G Networks

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

System model of THz-enabled UAVs network

✓ Problem Statement

- Next-generation networks need to meet ubiquitous and high data-rate demand
- Exploring THz-enabled UAVs to facilitate ubiquitous 6G mobile communication networks



S. S. Hassan, Y. M. Park, Y. K. Tun, W. Saad, Z. Han. and **C. S. Hong**, “3TO: THz-Enabled Throughput and Trajectory Optimization of UAVs in 6G Networks by Proximal Policy Optimization Deep Reinforcement Learning," IEEE International Conference on Communications 2022 (ICC 2022).

Summary of Investigations

- ✓ This work considers the throughput and trajectory optimization of terahertz (THz)-enabled unmanned aerial vehicles (UAVs)
  - That enables the ubiquitous demands in the sixth-generation (6G) communication networks.
- ✓ In the considered scenario, multiple UAVs must provide on-demand terabits per second (Tb/s) services to an urban area along with existing terrestrial networks
- ✓ However, THz-empowered UAVs pose some new constraints,
  - Dynamic THz-channel conditions for ground users (GUs) association and UAV trajectory optimization to fulfill GU's throughput demands
- ✓ Thus, a framework is proposed to address these challenges, where a joint UAVs-GUs association, transmit power, and the trajectory optimization problem is studied

S. S. Hassan, Y. M. Park, Y. K. Tun, W. Saad, Z. Han. and **C. S. Hong**, "3TO: THz-Enabled Throughput and Trajectory Optimization of UAVs in 6G Networks by Proximal Policy Optimization Deep Reinforcement Learning," IEEE International Conference on Communications 2022 (ICC 2022).

Goal is to maximize the total throughput from all the deployed UAVs while satisfying the QoS and trajectory constraints of each GU and UAV, respectively.

✓ The throughput maximization problem can be defined as follows:

$$R_{k,m}(n) = \alpha_{k,m} B_{k,m} \log_2 (1 + \gamma_{k,m})$$

$$\mathbf{P1:} \max_{\boldsymbol{\alpha}, \boldsymbol{p}, \boldsymbol{q}} \quad R_k^{\text{lo}}(n) \tag{5a}$$

s.t.

$$\sum_{n=1}^{N} \sum_{m=1}^{M} \alpha_{k,m} R_{k,m}(n) \geq R_k^{\text{lo}}(n), \ \forall k \in \mathcal{K}, \tag{5b}$$

$$\alpha_{k,m} R_{k,m}(n) \geq R^{\text{min}}, \ \forall m \in \mathcal{M}, k \in \mathcal{K}, n \in \mathcal{N}, \tag{5c}$$

$$\alpha_{k,m} \in \{0,1\}, \sum_{m=1}^{M} \alpha_{k,m} = 1, \ \forall k \in \mathcal{K}, m \in \mathcal{M}, \tag{5d}$$

$$\sum_{m=1}^{M} p_{k,m}(n) \leq P_k^{\text{max}}, \forall k \in \mathcal{K}, n \in \mathcal{N}, \tag{5e}$$

$$0 \leq p_{k,m}(n) \leq P_k^{\text{max}}, \forall k \in \mathcal{K}, n \in \mathcal{N}, \tag{5f}$$

$$\|\mathbf{q}_i(n) - \mathbf{q}_j(n)\|_2^2 \geq D_{\textbf{min}}^2, \forall i \neq j \in \mathcal{K}, \forall n \in \mathcal{N}, \tag{5g}$$

$$\frac{\|\mathbf{q}_k(n+1) - \mathbf{q}_k(n)\|}{t^{\text{mov}}} \leq V^{\textbf{max}}, \forall k \in \mathcal{K}, n \in \mathcal{N}, \tag{5h}$$

Association

Power

Trajectory

Optimization objective

QoS constraint

Each GU can be associated with at most one UAV

Total transmit power of the UAV have to be less than the maximum transmit power

Guarantees that the distance between UAVs is not as close as the minimum distance

UAVs speed constraint

S. S. Hassan, Y. M. Park, Y. K. Tun, W. Saad, Z. Han. and **C. S. Hong**, “3TO: THz-Enabled Throughput and Trajectory Optimization of UAVs in 6G Networks by Proximal Policy Optimization Deep Reinforcement Learning," IEEE International Conference on Communications 2022 (ICC 2022).

Proposed Solution

Balanced K-means Clustering (BKMC) for ground user associations

Algorithm 1 BKMC for GUs Association

Input: the GU locations $\{\mathbf{o}_m\}_{m\in\mathcal{M}}$, the initial UAV locations $\{\mathbf{q}_k\}_{k\in\mathcal{K}}$.
Initialize: Initialize centroid locations C^0 to UAV locations $\{\mathbf{q}_k\}_{k\in\mathcal{K}}$.
$t \leftarrow 0$
repeat
    Calculate distances between GUs and UAVs.
    Solve an assignment problem by Hungarian algorithm.
    Calculate new centroid locations C^{t+1}.
until the positions of the centroids do not change
Output: Optimal user association. $\boldsymbol{\alpha}^*$

Successive Convex Approximation (SCA) for transmit power allocation

$$\min_{\boldsymbol{p}} \quad -R_k^{\text{lo}}(n) \qquad (17a)$$

$$\text{s.t.} \quad (5b), (5e), \text{ and } (5f). \qquad (17b)$$

Algorithm 2 SCA for Transmit Power Optimization (17)

Input: $p_{k,m}^{\max}$, $\boldsymbol{p}^0$, iteration $j = 0$, tolerance χ, stopping criterion $e = 1$.
$j \leftarrow 0$
while e $\geq \chi$ **do**
    Designed $R(\boldsymbol{p},\boldsymbol{p}') = l(\boldsymbol{p}) - \tilde{h}((\boldsymbol{p},\boldsymbol{p}'))$ based on (12).
    Solve (17) and find the $\boldsymbol{p}^{j+1}$.
    Calculate the stopping criterion $e = |R(\boldsymbol{p}^{j+1}) - R(\boldsymbol{p}^j)|$.
    Update the iteration counter i.e., $j = j + 1$.
end while
Output: Optimal transmit power $\boldsymbol{p}^*$.

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S. S. Hassan, Y. M. Park, Y. K. Tun, W. Saad, Z. Han. and **C. S. Hong**, “3TO: THz-Enabled Throughput and Trajectory Optimization of UAVs in 6G Networks by Proximal Policy Optimization Deep Reinforcement Learning," IEEE International Conference on Communications 2022 (ICC 2022).

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Proposed solution

Proximal Policy Optimization Deep Reinforcement Learning for UAVs trajectory

Algorithm 3 PPO-DRL for UAVs Trajectory Optimization $\boxed{18}$

for episode= $1, 2, ..., E$ **do**
  Initialize randomly each GU's positions
  GUs Association $\boldsymbol{\alpha}$ by **Algorithm 1**
  for actor= $1, 2, ..., A$ **do**
    for time slot= $1, 2, ..., N$ **do**
      Run policy $\pi_{\theta_{\text{old}}}$ in environment
      Optimal Power Allocation $\boldsymbol{\mathcal{P}}$ by **Algorithm 2**
      Save (s_n, a_n, r_n, s_{n+1}) in Trajectory memory
    end for
    Compute advantage estimates $\hat{A}_1, ..., \hat{A}_N$
  end for
  Optimize surrogate L^{PPO} wrt θ, with minibatch from Trajectory memory
  $\theta_{\text{old}} \leftarrow \theta$
end for
Output: The optimal PPO network $\pi_{\theta_{\text{opt}}}$

$$\max_{\boldsymbol{q}} \quad R_k^{\text{lo}}(n) \qquad (18a)$$
$$\text{s.t.} \quad (5b), (5c), (5g), \text{ and } (5h). \qquad (18b)$$

- The state $s_t(n)$ in learning time step t:

$$s_t(n) = \{\{\mathbf{q}_k(n)\}_{k\in\mathcal{K}}, \{\mathbf{o}_m\}_{m\in\mathcal{M}}\}$$

Locations: UAV and user

- The action in learning step t at time slot n is the speed and the moving:

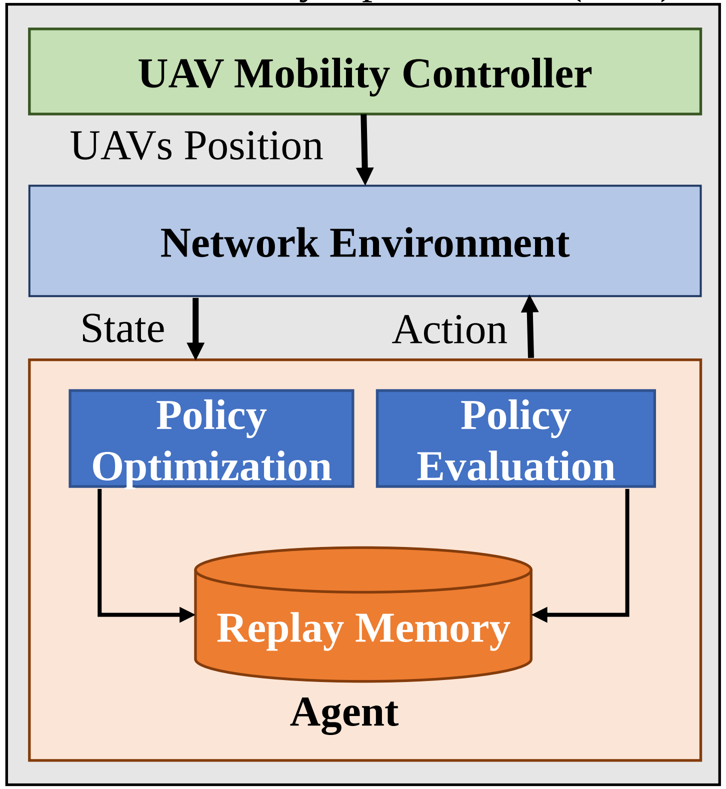
$$\{\{v_k(n), \phi_k(n)\}_{k\in\mathcal{K}}\}$$

Speed and moving direction

- The reward in learning step t at time slot n is divided into three:

$$r_t(n) = \begin{cases} 2, & \text{if } t = \max \text{ step}, \\ -2, & \text{if } \exists\ i, j \in \mathcal{K} \\ & \text{s.t. } \|\mathbf{q}_i(n) - \mathbf{q}_j(n)\| < D_{\min}, \\ \sum_{k=1}^{K} R_k^{\text{lo}}(n), & \text{otherwise.} \end{cases}$$

Proximal Policy Optimization (PPO)



$$\hat{E}_t\left[\min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t)\right]$$

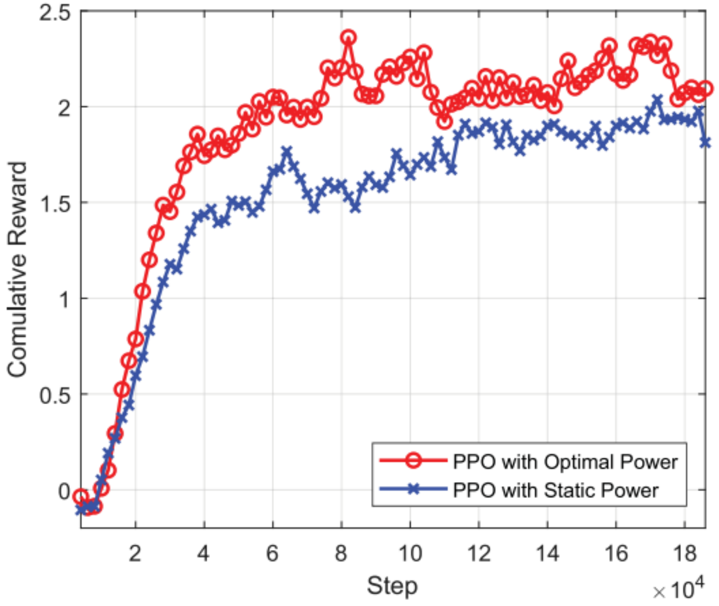
S. S. Hassan, Y. M. Park, Y. K. Tun, W. Saad, Z. Han. and **C. S. Hong**, "3TO: THz-Enabled Throughput and Trajectory Optimization of UAVs in 6G Networks by Proximal Policy Optimization Deep Reinforcement Learning," IEEE International Conference on Communications 2022 (ICC 2022).

Simulation Results

- To assess the performance of our proposed algorithm, we consider four benchmark algorithms as follows:
  - SU with RP: The algorithm which considers static UAVs (SU) positions with the random power (RP) allocation.
  - OU with RP: The algorithm uses the optimal UAVs (OU) trajectory with the random power (RP) allocation.
  - SU with PP: The algorithm assumes the static UAVs (SU) positions with the proposed power (PP) allocation.
  - OU with PP (proposed method): The algorithm considers the optimal UAV (OU) trajectory with the proposed power (PP) allocation.

TABLE I: Simulation Parameters

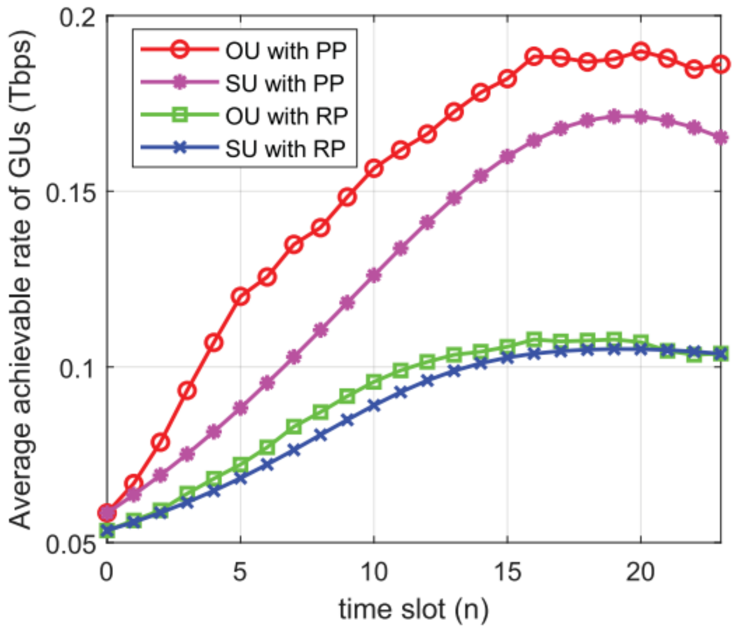
Parameter	Value	Parameter	Value
Bandwidth	B=0.1 THz	Channel gain at ref.	h_0=−40 dBm
Noise power	σ^2=−174 dBm/Hz	Max. transmit power	$P^{\max}$=2 W
Minimum rate	$R^{\min}$=0.02 Tbps	Absorption coefficient	$a(f)$=0.005
Episodes	E=5e + 5	Batch size	120
Discount factor	γ =0.99	Learning rate	0.0003
Clipping ϵ	0.2	Regularizer parameter	λ = 0.95
Epochs	3	Hidden layer's units	128
Hidden layers	2	Carrier Frequency	f=1.2 THz [13]



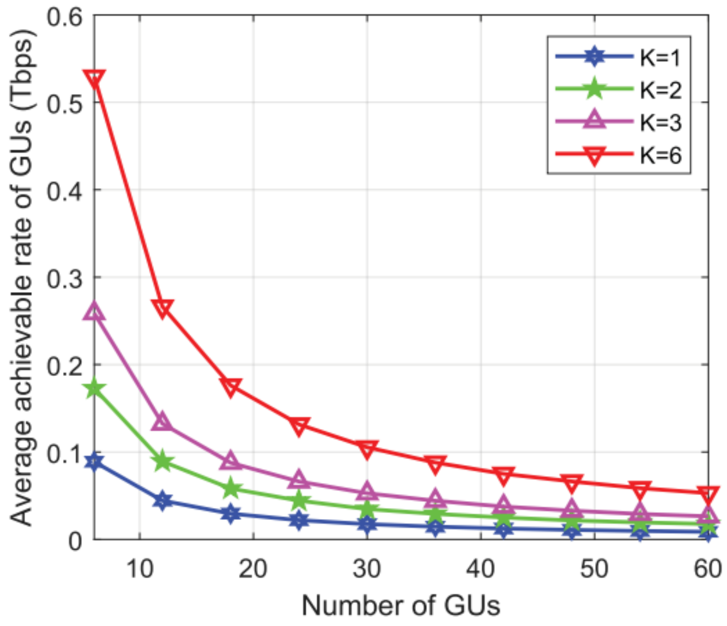
Proximal policy optimization deep reinforcement learning (PPODRL) learning results (reward)

S. S. Hassan, Y. M. Park, Y. K. Tun, W. Saad, Z. Han. and **C. S. Hong**, "3TO: THz-Enabled Throughput and Trajectory Optimization of UAVs in 6G Networks by Proximal Policy Optimization Deep Reinforcement Learning," IEEE International Conference on Communications 2022 (ICC 2022).

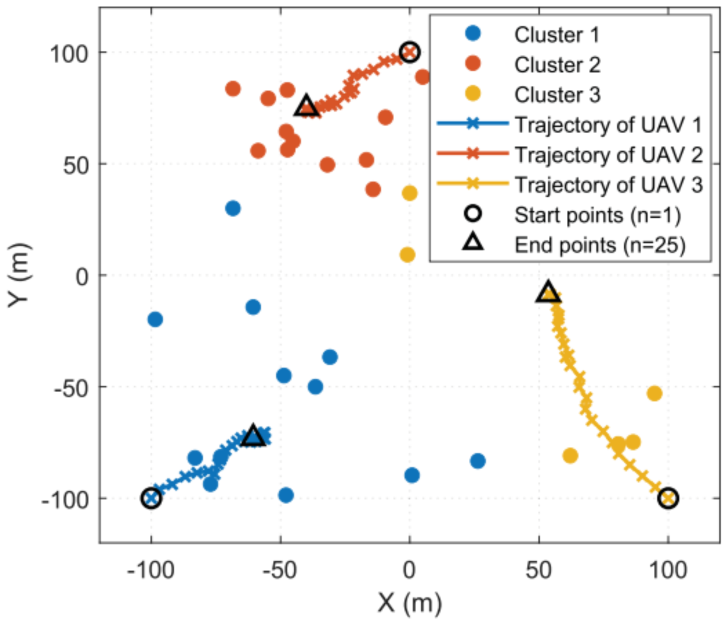
Simulation Results



Achievable rate with benchmarks schemes



Achievable rate with UAVs



UAVs trajectory obtained by proximal policy optimization deep reinforcement learning

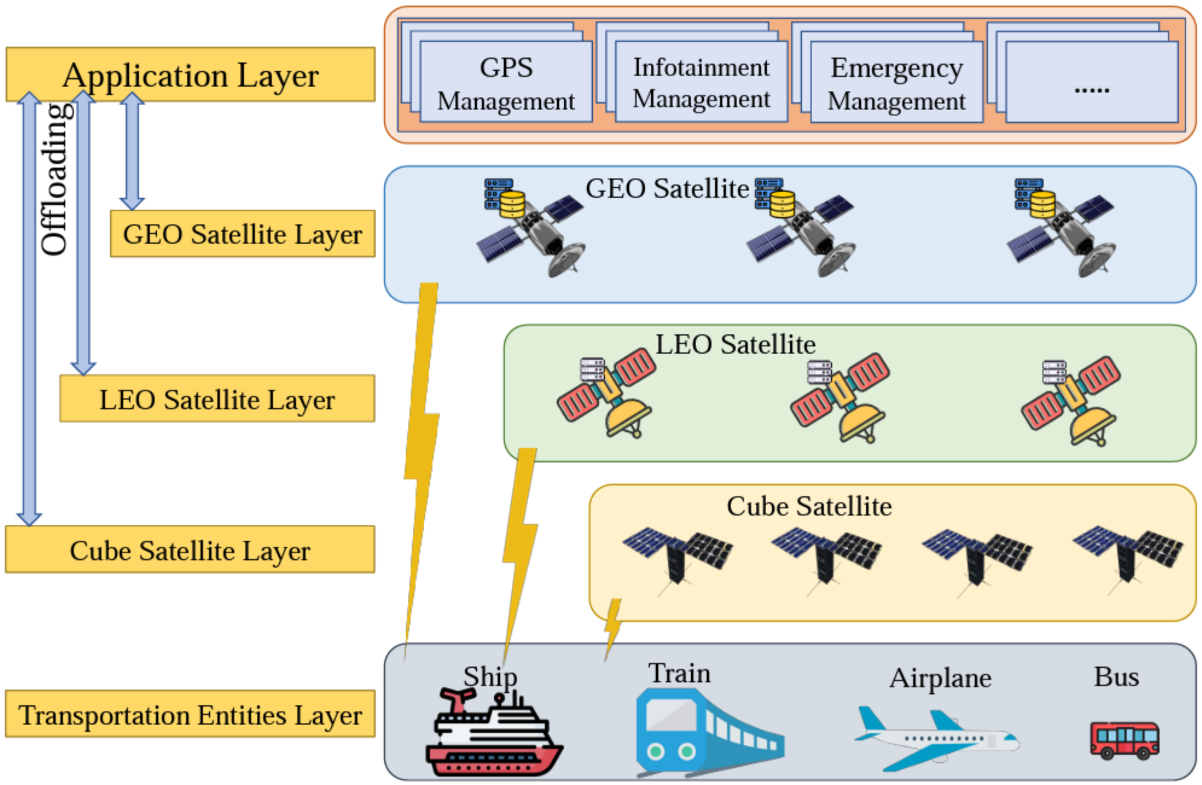
S. S. Hassan, Y. M. Park, Y. K. Tun, W. Saad, Z. Han. and **C. S. Hong**, "3TO: THz-Enabled Throughput and Trajectory Optimization of UAVs in 6G Networks by Proximal Policy Optimization Deep Reinforcement Learning," IEEE International Conference on Communications 2022 (ICC 2022).

Use Case 6: Satellite-based ITS Data Offloading & Computation in 6G Networks

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

System model for ITS data offloading & computation

- A service architecture for data-driven ITS task offloading and computation to MEC-enabled diverse satellite networks is studied.
- A joint delay and rental price minimization problem for different satellite servers while optimizing offloading task selection, computing, and bandwidth resource allocation.
- To handle the formulated mixed-integer non-linear programming (MINLP) problem, which is NP-hard, we propose a two-stage algorithm based on the Co-MAPPO DRL algorithm in cooperation with the attention approach and convex theory.



ITS: Intelligent transportation systems
MAPPO: Multi-agent proximal policy optimization

Hassan, S. S., Park, Y. M., Tun, Y. K., Saad, W., Han, Z., & **Hong, C. S.** (2022). Satellite-based ITS Data Offloading & Computation in 6G Networks: A Cooperative Multi-Agent Proximal Policy Optimization DRL with Attention Approach", Submitted Revision to IEEE Transactions on Mobile Computing (TMC). Available at: https://doi.org/10.48550/arXiv.2212.05757

Optimization problem formulation for ITS task offloading

Weighted sum of mean service time and price

Mean Service Time

Mean Service Price

CTEs: Crowed-sourced Transportation Entities
CNS: Core Network Server
LMS: LEO satellite-based MEC server

Offloading decisions

Communication bandwidth allocation

Computing resource allocation

GEO-based Computing resource allocation

$$\mathbf{P1:} \quad \min_{\underbrace{\mathbf{X},\mathbf{Y},\boldsymbol{\beta},\boldsymbol{\omega}}} \quad \boxed{\eta} = \sum_{\forall \mu \in \mathcal{D}} \frac{\alpha_1 T_d^{\text{ser}} + \alpha_2 P_d^{\text{ser}}}{\boxed{\|D\|}} \tag{16a}$$

Number of tasks

s.t.

$$\sum_{\forall b \in \mathcal{B}} x_{d_\mu}^b = 1, \ \forall d \in \mathcal{D}, \ \forall \mu \in \mathcal{E}, \tag{16b}$$

Summation of associated CTE will be one at each time slot.

$$\sum_{\forall d \in \mathcal{D}} \sum_{\forall \mu \in \mathcal{E}_l} x_{d_\mu}^b y_{d_\mu}^b \leq 1, \ \forall b \in \mathcal{B}, \tag{16c}$$

Total wireless bandwidth allocation ratio is less than or equal to one.

$$\sum_{\forall d \in \mathcal{D}} \sum_{\forall \mu \in \mathcal{E}_l} x_{d_\mu}^b \beta_{d_\mu}^b \leq \varrho_b, \ \forall b \in \mathcal{B}, \tag{16d}$$

Allocated LMS and CubeSats computing resources do not exceed the threshold.

$$x_{d_\mu}^b \{T_{d_\mu,b}^{\text{tran}} + T_{d_\mu,b}^{\text{comp}}\} \leq T_{d_\mu,b}^{\max}, \ \forall b \in \mathcal{B}, \tag{16e}$$

Communication time between CTE and related satellite is shorted than the maximum permitted time.

$$\sum_{\forall d \in \mathcal{D}} \sum_{\forall \mu \in \mathcal{E}_c} x_{d_\mu}^b \leq 1, \ \forall b \in \mathcal{C}_l, \tag{16f}$$

Only those CubeSats that are already in the neighborhood of LMS *l* can give services to CTE.

$$x_{d_\mu}^b \in \{0,1\}, \ \forall b \in \mathcal{B}_\mu, \ \forall d_\mu \in d, \ \forall d \in \mathcal{D}, \tag{16g}$$

Each CTE can only associate with one satellite at a time.

$$\omega_{d_\mu}^h \in R^+, \ \forall d_\mu \in d, \ \forall d \in \mathcal{D}., \tag{16h}$$

Ensures that each CNS *h has enough computing resources.*

$$y_{d_\mu}^b \leq Y^{\text{th}}, \ \forall b \in \mathcal{B}, \tag{16i}$$

Ensures that bandwidth resources remains within the budget for each satellite.

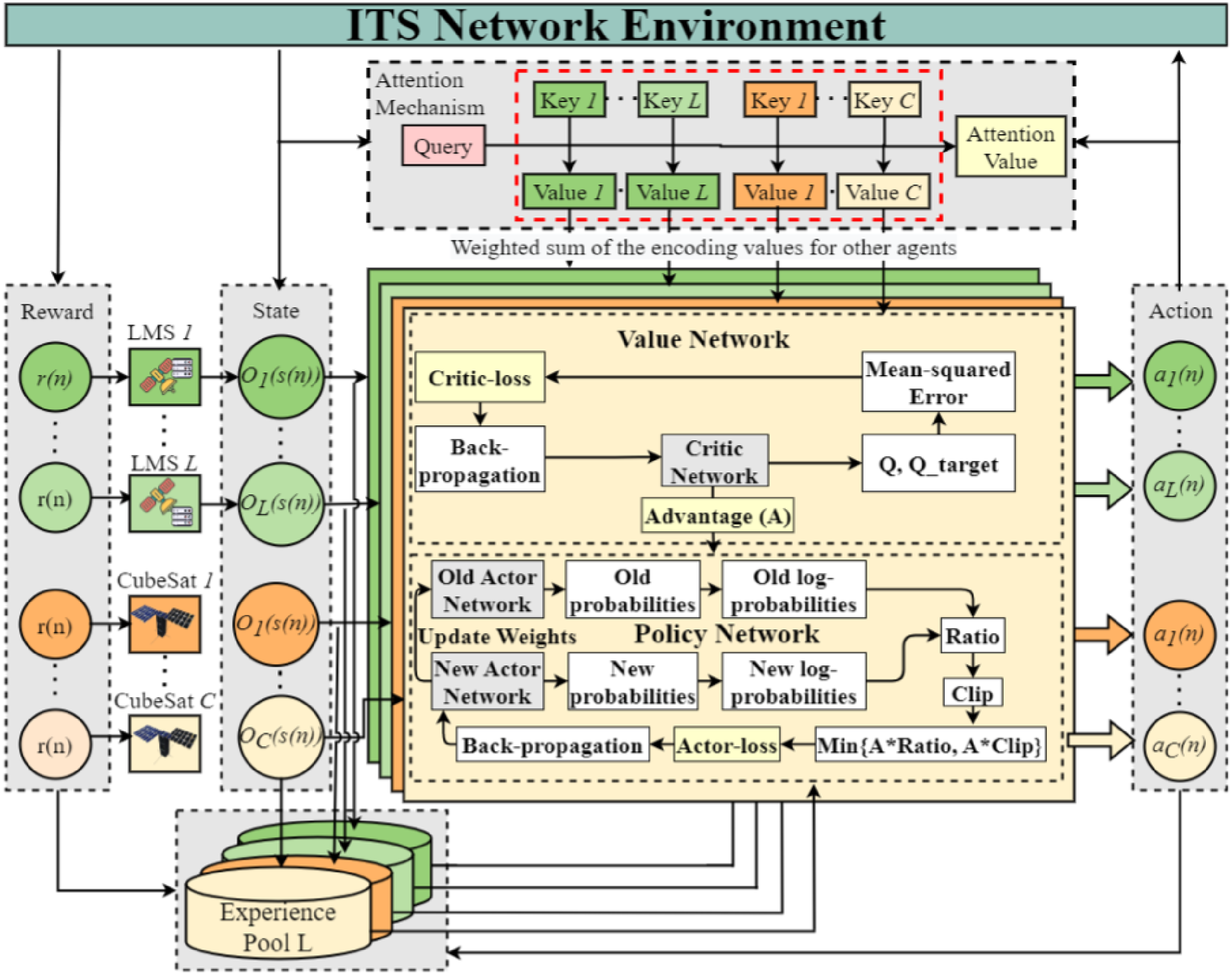
$$\beta_{d_\mu}^b \leq \beta^{\text{th}}, \ \forall b \in \mathcal{B}. \tag{16j}$$

Ensures that bandwidth resources remain within the budget for each satellite.

Hassan, S. S., Park, Y. M., Tun, Y. K., Saad, W., Han, Z., & **Hong, C. S.** (2022). Satellite-based ITS Data Offloading & Computation in 6G Networks: A Cooperative Multi-Agent Proximal Policy Optimization DRL with Attention Approach“, Submitted Revision to IEEE Transactions on Mobile Computing (TMC). Available at: https://doi.org/10.48550/arXiv.2212.05757

Proposed framework of Co-MAPPO DRL with Attention mechanism for ITS task offloading

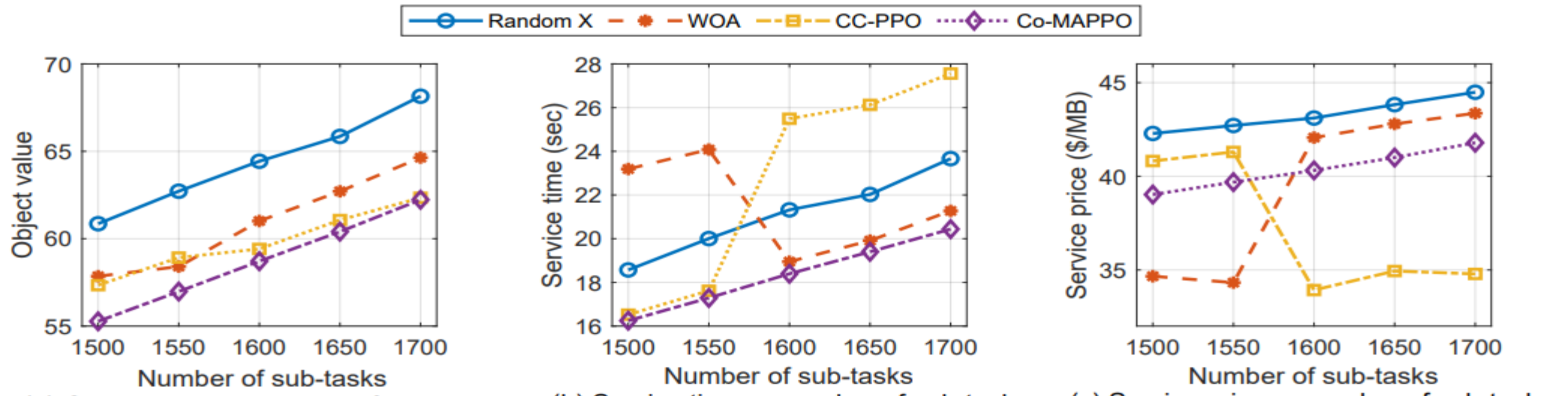
- We introduced the ability to respond to situations in which the number of connected CTEs dynamically changes.
- Since the input size of the general NN model is fixed, we cannot effectively respond to the changing CTEs information we want.
- Thus we proposes a learning network model regardless of the number of connected CTEs by adding attention in front of the input layer.



CTEs: Crowed-sourced Transportation Entities

Hassan, S. S., Park, Y. M., Tun, Y. K., Saad, W., Han, Z., & **Hong, C. S.** (2022). Satellite-based ITS Data Offloading & Computation in 6G Networks: A Cooperative Multi-Agent Proximal Policy Optimization DRL with Attention Approach", Submitted Revision to IEEE Transactions on Mobile Computing (TMC). Available at: https://doi.org/10.48550/arXiv.2212.05757

Experimental Results



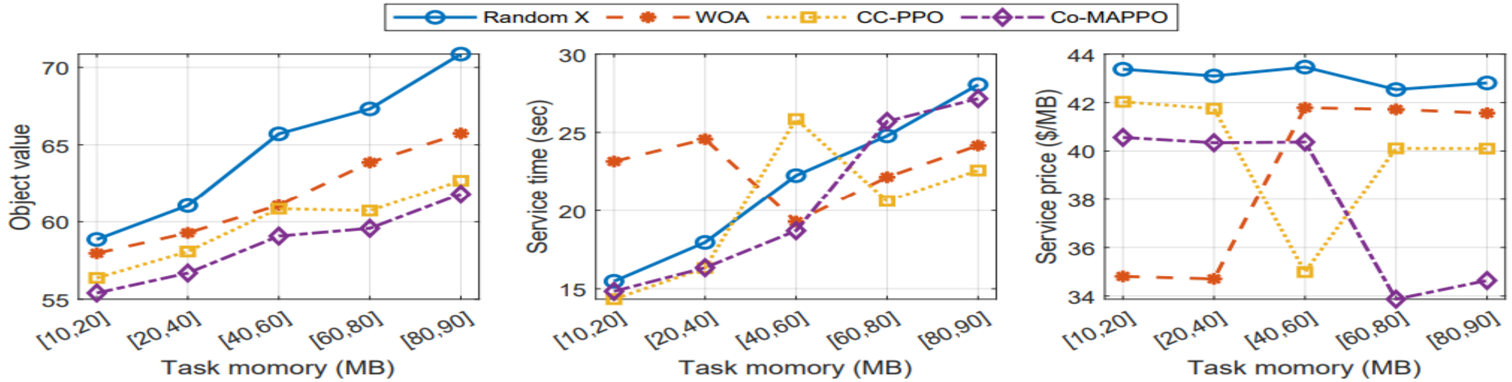
(a) Object value vs number of sub-tasks (b) Service time vs number of sub-tasks (c) Service price vs number of sub-tasks

Figure 7: Comparison with benchmarks schemes for various number of sub-tasks.

Objective value comparison of Co-MAPPO with benchmarks schemes for various sub-tasks.

Service Time vs varying number of sub-tasks.

Service Price vs varying number of sub-tasks.



(a) Object value vs size of task memory (b) Service time vs size of task memory (c) Service price vs size of task memory

Figure 8: Comparison with benchmarks schemes for various task memory.

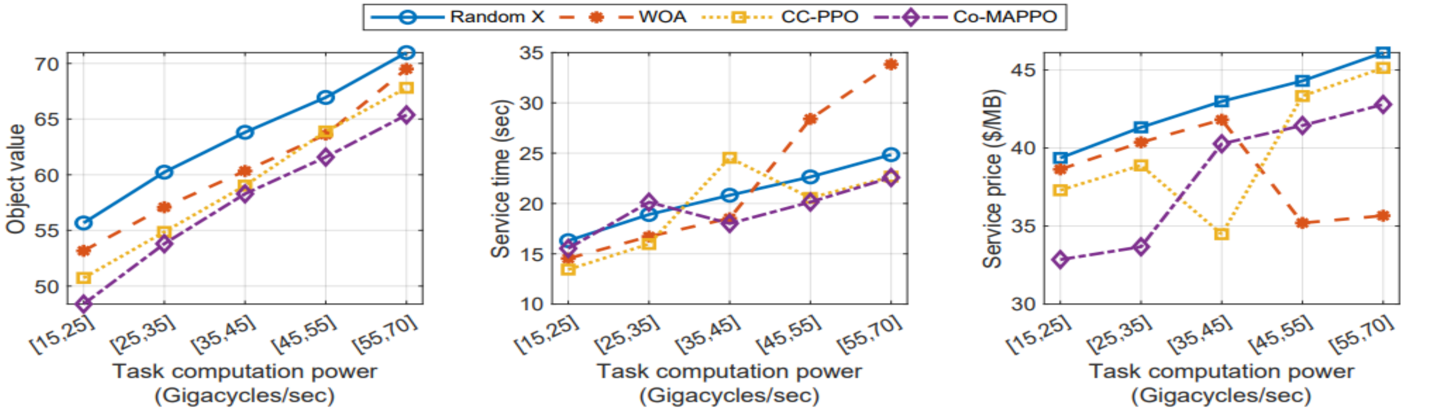
Objective value comparison of Co-MAPPO with benchmarks schemes for varying task memory.

Service time vs varying task memory.

Service Price vs varying task memory.

Hassan, S. S., Park, Y. M., Tun, Y. K., Saad, W., Han, Z., & **Hong, C. S.** (2022). Satellite-based ITS Data Offloading & Computation in 6G Networks: A Cooperative Multi-Agent Proximal Policy Optimization DRL with Attention Approach“, Submitted Revision to IEEE Transactions on Mobile Computing (TMC). Available at: https://doi.org/10.48550/arXiv.2212.05757

Experimental Results



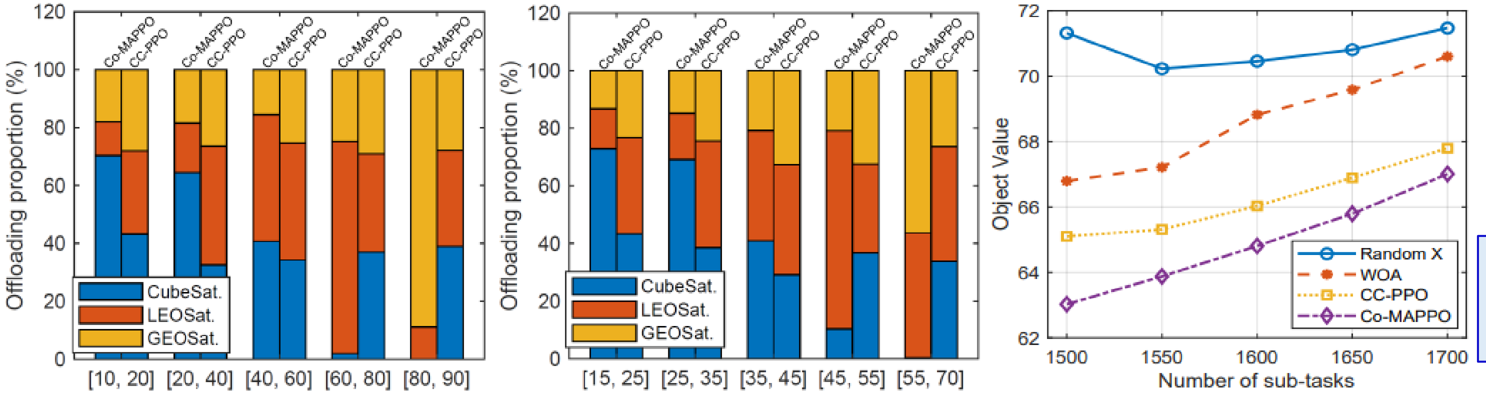
(a) Object value vs task computation power (b) Service time vs task computation power (c) Service price vs task computation power

Figure 9: Comparison with benchmarks schemes for various task computation power.

Objective value comparison of Co-MAPPO with benchmarks schemes for varying task computation power.

Service time vs varying computation power.

Service Price vs varying computation power.



(a) Sub-tasks offloading proportion according to the varying computing memory. (b) Sub-tasks offloading proportion according to the varying computing power. (c) Comparison with non convex optimization for various sub-tasks (ablation study).

Figure 10: Illustration of proportional data offloading with various satellites and non-convex optimization comparison.

Objective value comparison with baselines without convex optimization part (only DRL)

Offloading proportion vs computing memory

Offloading proportion vs computing power.

Hassan, S. S., Park, Y. M., Tun, Y. K., Saad, W., Han, Z., & **Hong, C. S.** (2022),"Satellite-based ITS Data Offloading & Computation in 6G Networks: A Cooperative Multi-Agent Proximal Policy Optimization DRL with Attention Approach", Submitted Revision to IEEE Transactions on Mobile Computing (TMC). Available at: https://doi.org/10.48550/arXiv.2212.05757

Challenges and Ongoing Research

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.

Satellite Communications and AI

- ✓ Constellation's resources problems
  - Routing among satellites
  - Beam placement and beam shaping
  - Frequency assignment
  - Power allocation
  - Federated Learning for resource sharing
  - RIS based beamforming
- ✓ Limitations due to interactions
  - Long-horizon forecasting in LEO environment
  - Multiuser demand prediction
  - Search space complexity
- ✓ New AI models and architecture
  - Transfer learning for satellite architectures
  - New prediction models for intra-orbit resource management
  - AI model for orbits as resources
  - Collaborative multiagent systems for end-to-end service management

Thanks for your attention!!!

- Q&A