Mobile Edge Computing and Communications from the Sky

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Agenda

- Mobile Edge Computing and Communications （MECC）
- Unmanned Aerial Vehicles (UAV)
- MECC+UAV

- Q&A

Tactile Internet

Our current Internet can support text, voice, video (triple play) quite well.
But not touch (haptic) or smell!

Hearing: 100ms Vision: 10ms Touch: 1ms

RTT=1ms

1msx($3x10^8$m/s)
=300km

Three Driving Forces

Service Providers

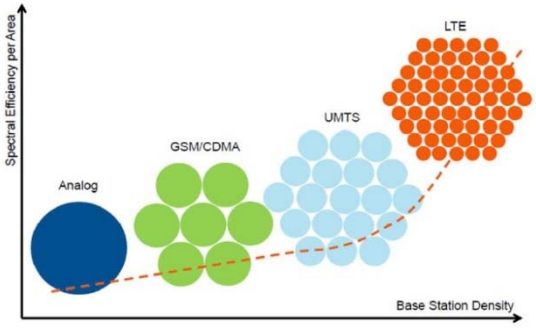
- Tactile Internet: Ultra-low latency (1ms)
- IoT Massive Connectivity
- Data privacy
- New services: 3D/VR/AR, interactive gaming, etc.

Mobile Operators

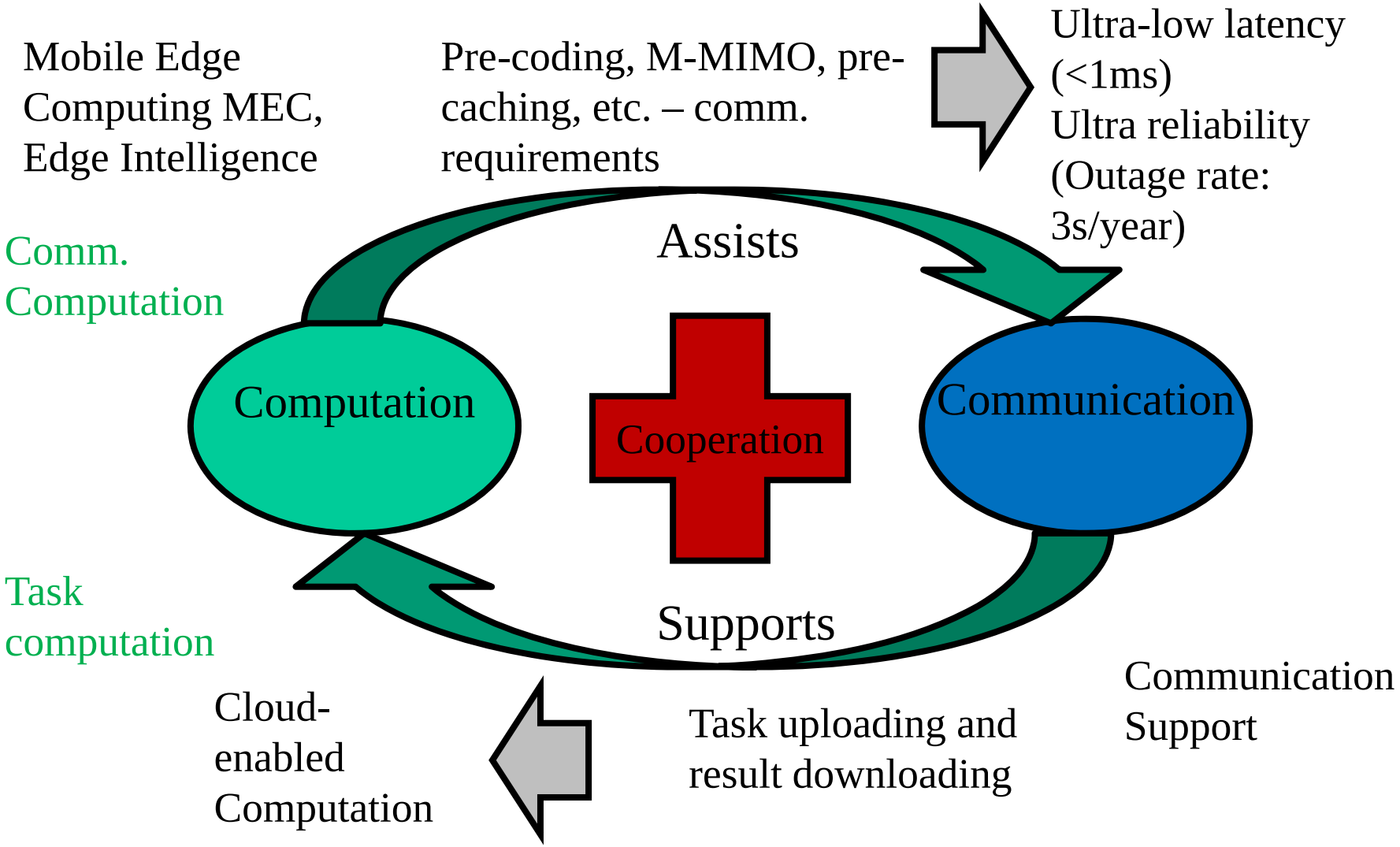
- Scarce spectrum mismatches increasing traffic
- Huge energy consumption
- Small cell issues
- Versatile vendor protocols

Mobile End Users

- Mobile phones running out battery soon
- Real-time responses
- Limited capacity of mobile terminals in terms of processing, memory, etc

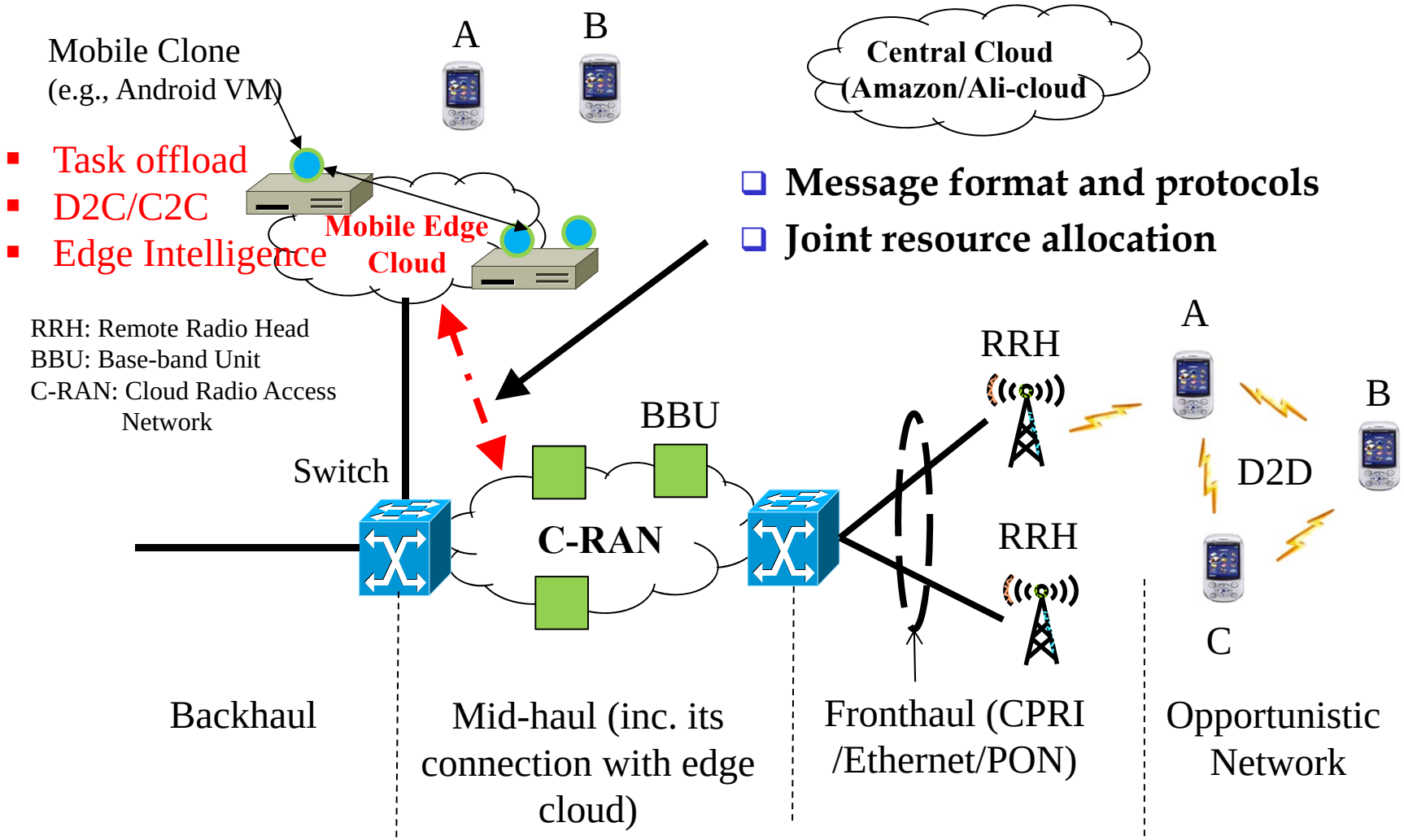


Overall Solution: 3C at Edge



System Architecture:

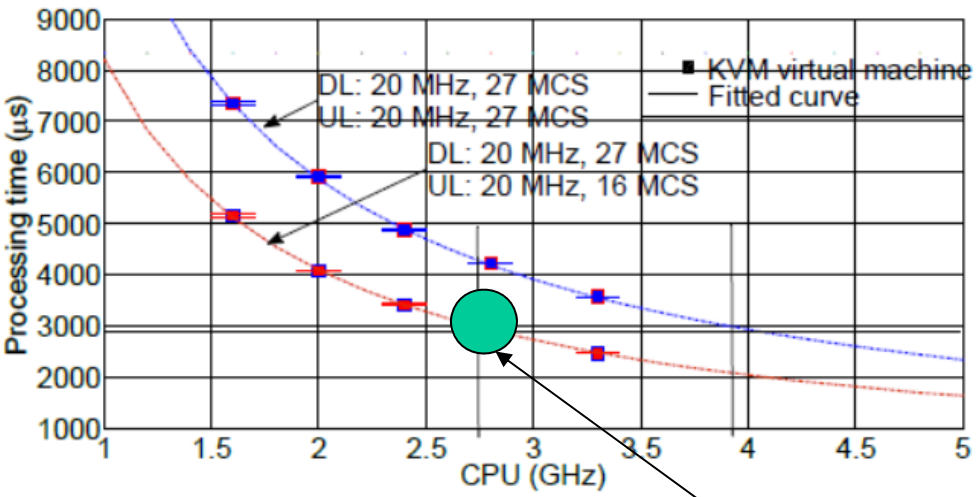
Virtualization of both networks and terminals



- Task offload
- D2C/C2C
- Edge Intelligence

- **Message format and protocols**
- **Joint resource allocation**

Computation Capacity vs Communication Quality



Experiments

LTE RTT: 8ms
=5ms (signal transmission) +3ms (signal processing)

*Navid Nikaein, Raymond Knopp, Chih-Lin I, Jinri Huang, and Duan Ran, Tutorial T-17: Cloud Radio Access Networks: Principles, Challenges, and Technologies, IEEE ICC 2015, June 2015, London, UK.

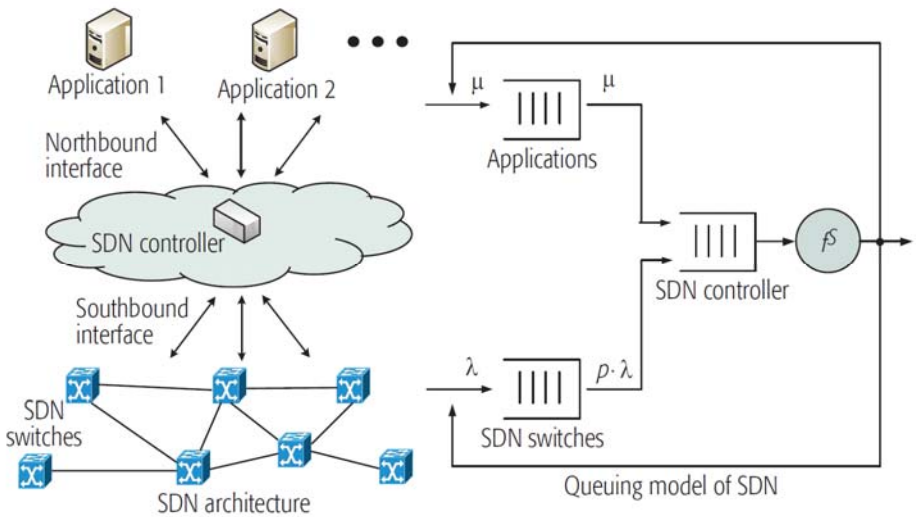
To finish signal processing within 3ms, at least 2.7GHz CPU processing capacity is needed*

Scenario-specific experimental formula: ** $P_{u,t} = \left(30A_{u,t} + 10A_{u,t}^2 + 20\frac{M_{u,t}}{6}C_{u,t}L_{u,t}\right)\cdot\frac{R_{u,t}}{50}$

Unit：GOPS

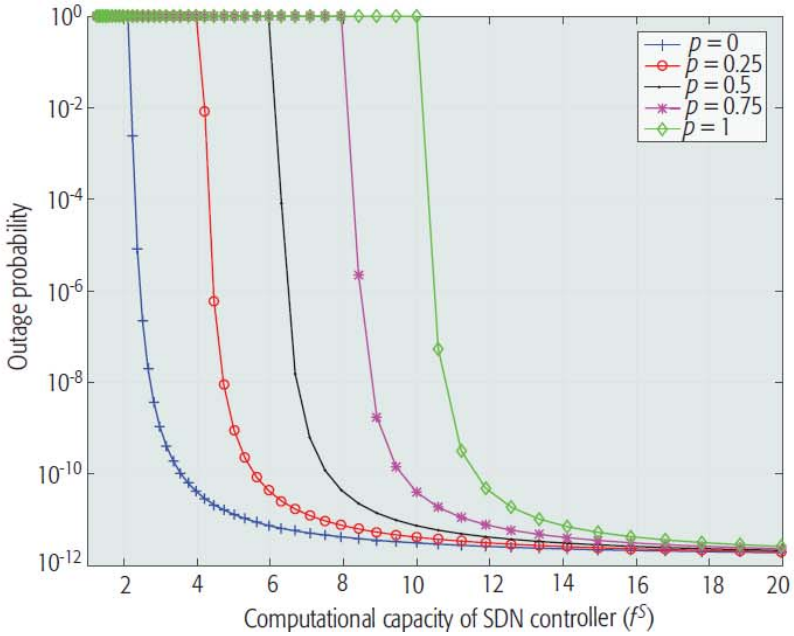
**T. Werthman, H. Grob-Lipski, M. Proebster. “Multiplexing Gains Achieved in Pools of Baseband Computation Units in 4G Cellular Networks”. IEEE PIMRC 2013, Pages: 3328 – 3333, 2013.

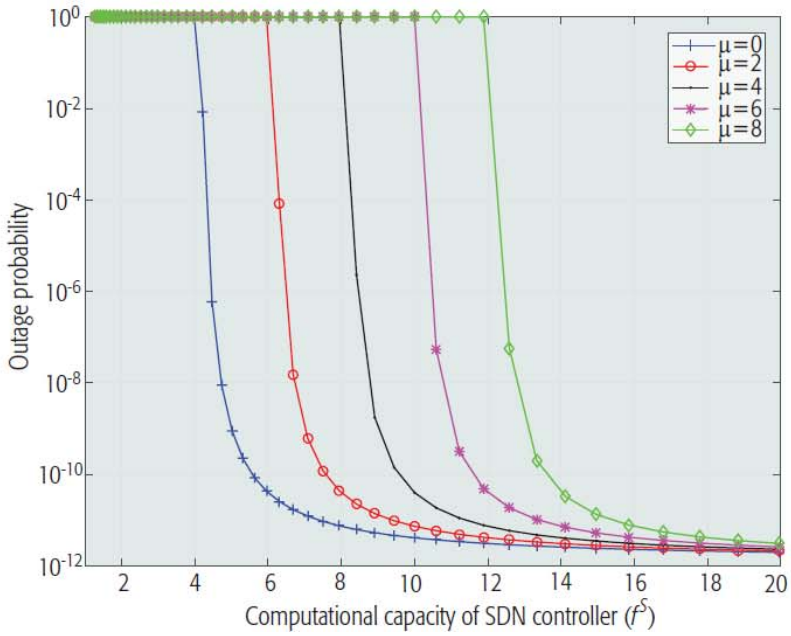
Computation on SDN Networks



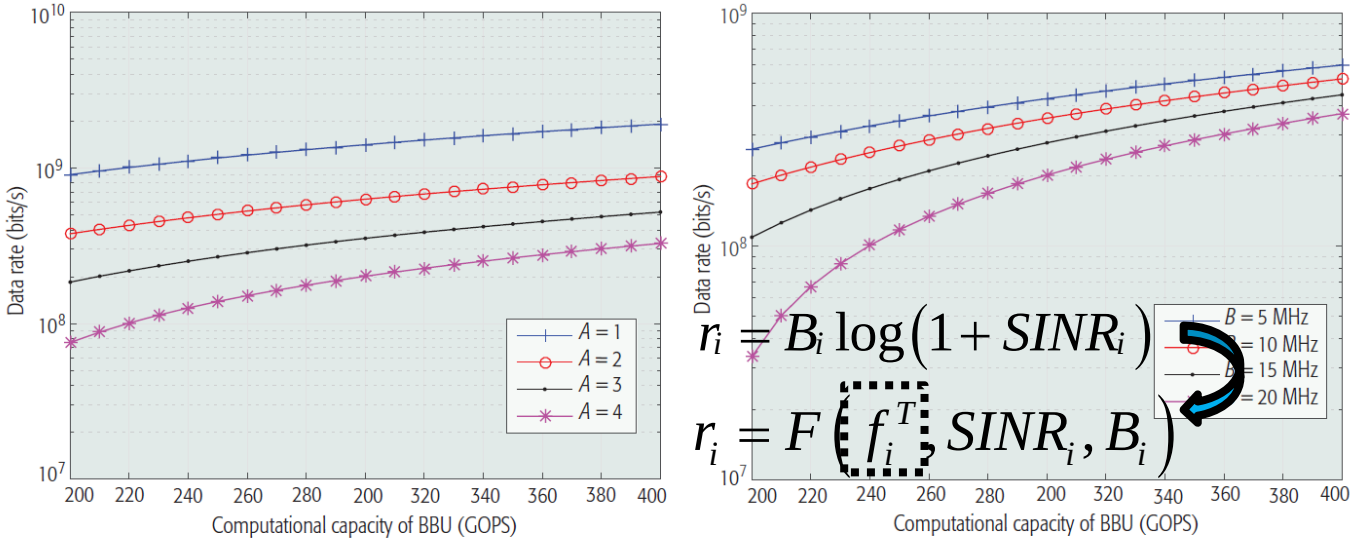
$$P^O = 1 - Q\left(\frac{\frac{1}{f^S - p\cdot\lambda - \mu} - \rho}{\sigma^2}\right).$$

Outage probability





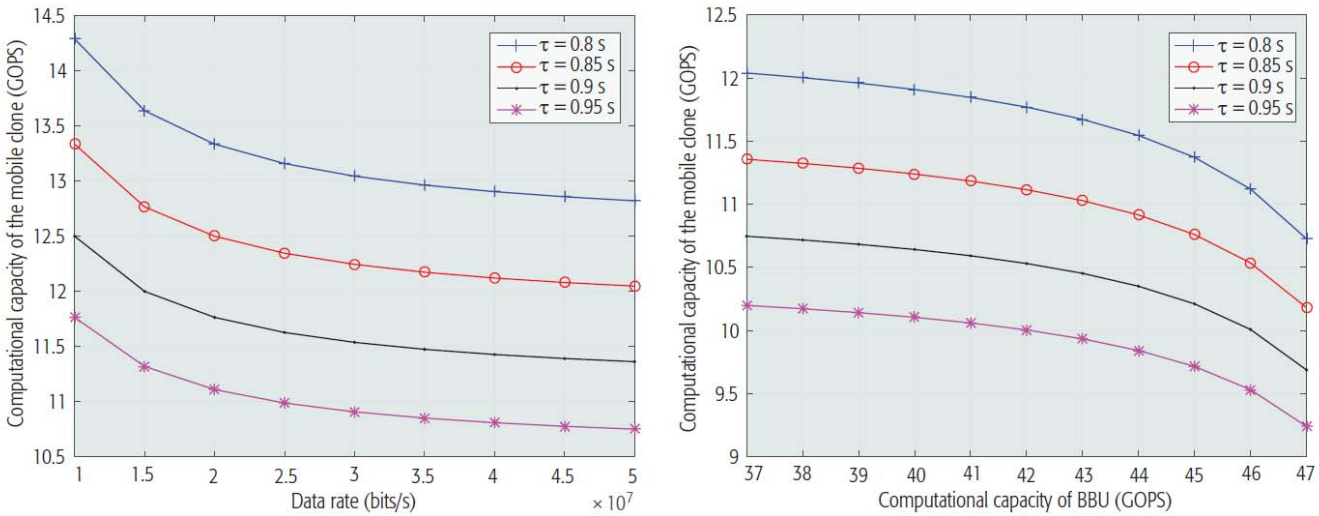
Computation on C-RAN and Mobile Clone



$$r_i = B_i \log(1 + SINR_i)$$

$$r_i = F(f_i^T, SINR_i, B_i)$$

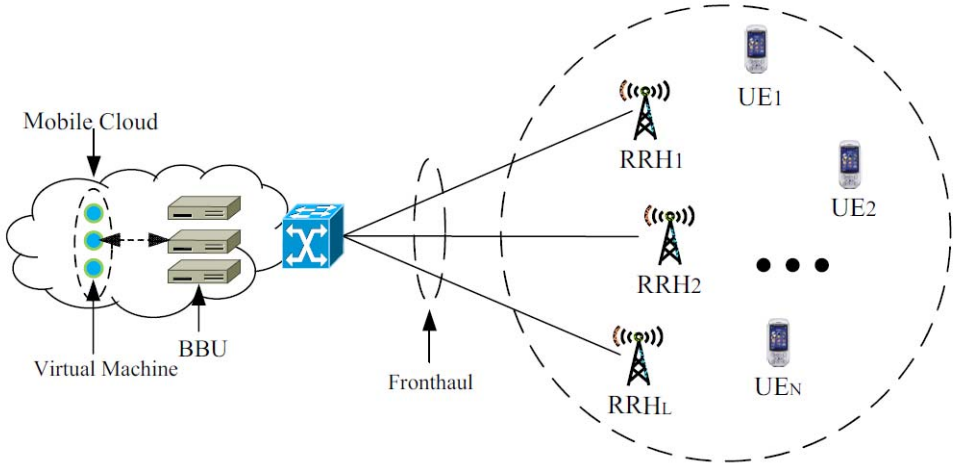
C-RAN



Mobile Clone

K. Wang, K. Yang, et al. "Computation Diversity in Emerging Networking Paradigms", IEEE Wireless Communications, Year: 2017 | Volume: 24, Issue: 1

System Model



- Consider there are $\mathcal{N} = \{1, 2, ..., N\}$ UEs and $\mathcal{L} = \{1, 2, ..., L\}$ RRHs , each of which has $K \geq 1$ antennas.
- The mobile cloud is co-located with the BBU and is responsible for computational intensive tasks offloaded by UEs.
- BBU is in charge of returning the execution results to the UE via RRHs.
- Assume each of UE i has the computational intensive task $U_i = (F_i, D_i),\ i = 1, 2, ..., N$ to be accomplished in the mobile cloud.

K. Wang, C. Magurawalage, K. Yang. “Joint Energy Minimization and Resource Allocation in C-RAN with Mobile Cloud”, IEEE Transactions on Cloud Computing, Year: 2018 , Volume: 6 , Issue: 3, Page s: 760 - 770

Computation and Communication Models

Task *i (each UE has only one task)*: $U_i = (F_i, D_i),\ i = 1, 2, ..., N$

- Time spent to complete this task: $T_i^C = \frac{F_i}{f_i^C}$
- Energy consumption: $E_i^C = \kappa_i^C (f_i^C)^{\nu_i^C - 1} F_i$
- Computation capacity constraint: $f_i^C \leq f_{i,max}^C$

VM CPU capacity

- UE *i* data rate: $r_i = B_i \log(1 + \mathrm{SINR}_i)$
- Time cost: $T_i^{Tr} = \frac{D_i}{r_i}$
- Energy consumption: $E_i^{Tr} = p_i \cdot T_i^{Tr} = \frac{p_i D_i}{r_i}$, where $p_i = \sum_{j \in \mathcal{C}} |\mathbf{v_{ij}}|^2$, $\mathbf{v_{ij}}$ is the beamforming vector from *j*-th RRH to the *i*-th UE, $\mathcal{C}$ is the RRH cluster serving the UE.

Of length *k*

- Power constraint for each RRH *j*: $\sum_{i=1}^{N} |\mathbf{v_{ij}}|^2 \leq P_j, \quad j = 1, 2, ..., L.$

Maximum power for RRH *j*.

QoS Requirement

RRH *j* is not serving UE *i*

- Fronthaul capability: $C_j = \sum_{i=1}^{N} ||\mathbf{v_{ij}}|^2|_0 \cdot r_i$ $\quad ||\mathbf{v_{ij}}|^2|_0 = \begin{cases} 0, \text{if } |\mathbf{v_{ij}}|^2 = 0 \\ 1, \text{otherwise} \end{cases}$.

- Fronthaul constraint: $C_j \leq C_{j,max}$

- Total time cost: $T_i = T_i^{Tr} + T_i^C$

Task *i* execution deadline

- Time constraint: $T_i \leq T_{i,max}$

Scaling factor

- Total energy cost: $E_i = E_i^C + \eta_i E_i^{Tr}$

Joint Optimization Problem

$$\underset{f_i^C, r_i, \mathbf{v_{ij}}, \mathcal{C}}{\text{minimize}} \quad \sum_{i=1}^{N} E_i^C + \eta_i E_i^{Tr}$$

Minimize the computation and communication energy

subject to

$$f_i^C \leq f_{i,max}^C, \quad i = 1, 2, ..., N,$$

Cloud computation constraints (CPU cycles/frequency)

$$\sum_{i=1}^{N} |\mathbf{v_{ij}}|^2 \leq P_j, \quad j = 1, 2, ..., L.$$

RRH Power constraints

$$\sum_{i=1}^{N} ||\mathbf{v_{ij}}|^2|_0 \cdot r_i \leq C_{j,max}, \quad j = 1, 2, ..., L.$$

Frouthaul constraints

$$r_i \geq R_{i,min}, \quad i = 1, 2, ..., N,$$

Achievable rate constraints

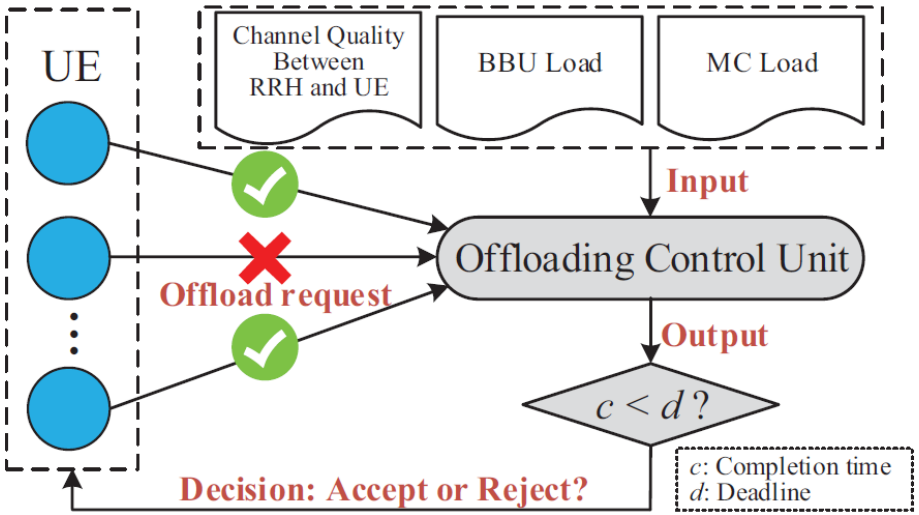
$$T_i^C + T_i^{Tr} \leq T_{i,max}, \quad i = 1, 2, ..., N,$$

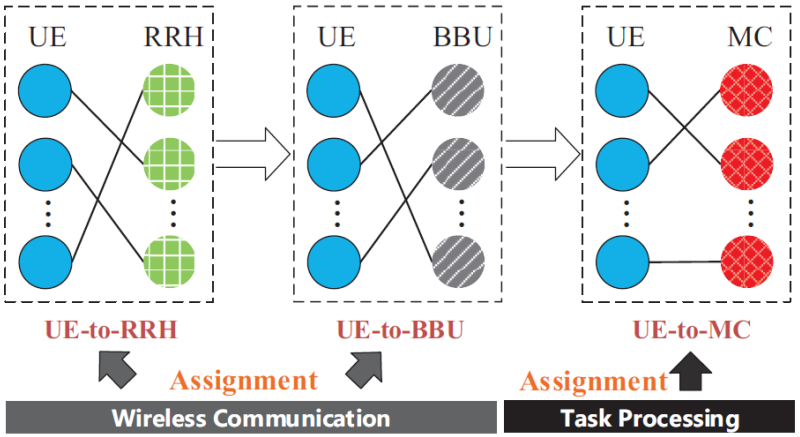
QoS constraints

- Non-convex problem
- Transform to weighted minimum mean square error (WMMSE) solution
- An iterative algorithm to solve this problem

K. Wang, C. Magurawalage, K. Yang. “Joint Energy Minimization and Resource Allocation in C-RAN with Mobile Cloud”, IEEE Transactions on Cloud Computing, Year: 2018 , Volume: 6 , Issue: 3, Page s: 760 - 770

Offload or Not?





Decision Making

$$\min \quad \sum_{u \in \mathcal{U}} \{c_u - d_u\}^+ \tag{6}$$

$$\text{s.t.} \quad \sum_{v \in \mathcal{V}} x_{uv}, \sum_{b \in \mathcal{B}} y_{ub}, \sum_{l \in \mathcal{L}} z_{ul} = 1 \quad \forall u \in \mathcal{U} \tag{7}$$

$$\sum_{u \in \mathcal{U}} x_{uv} \leq \gamma_v - \gamma_v^0, \quad \forall v \in \mathcal{V} \tag{8}$$

$$\sum_{u \in \mathcal{U}} y_{ub} \leq \gamma_b - \gamma_b^0, \quad \forall b \in \mathcal{B} \tag{9}$$

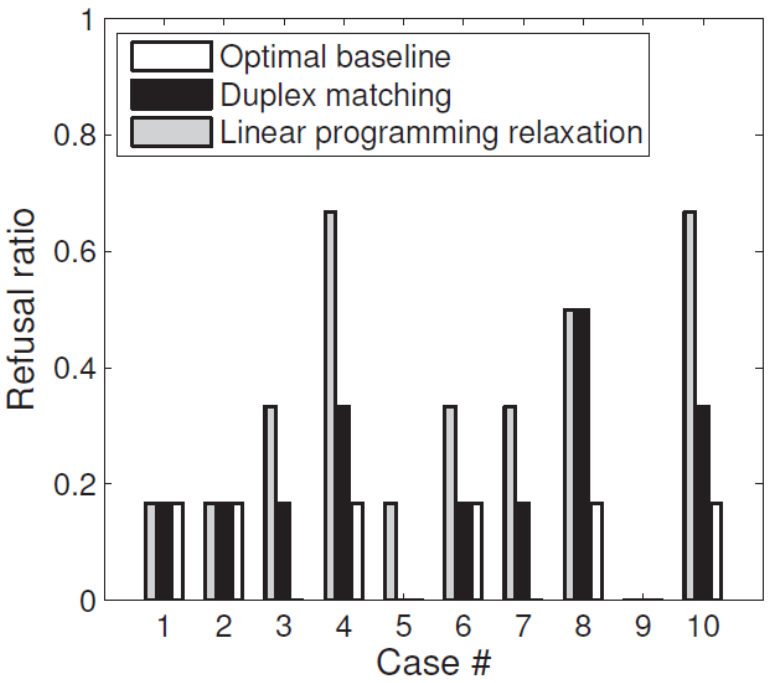
$$x_{uv}, y_{ub}, z_{ul} = 0 \text{ or } 1, \quad \forall u \in \mathcal{U}, v \in \mathcal{V}, b \in \mathcal{B} \tag{10}$$

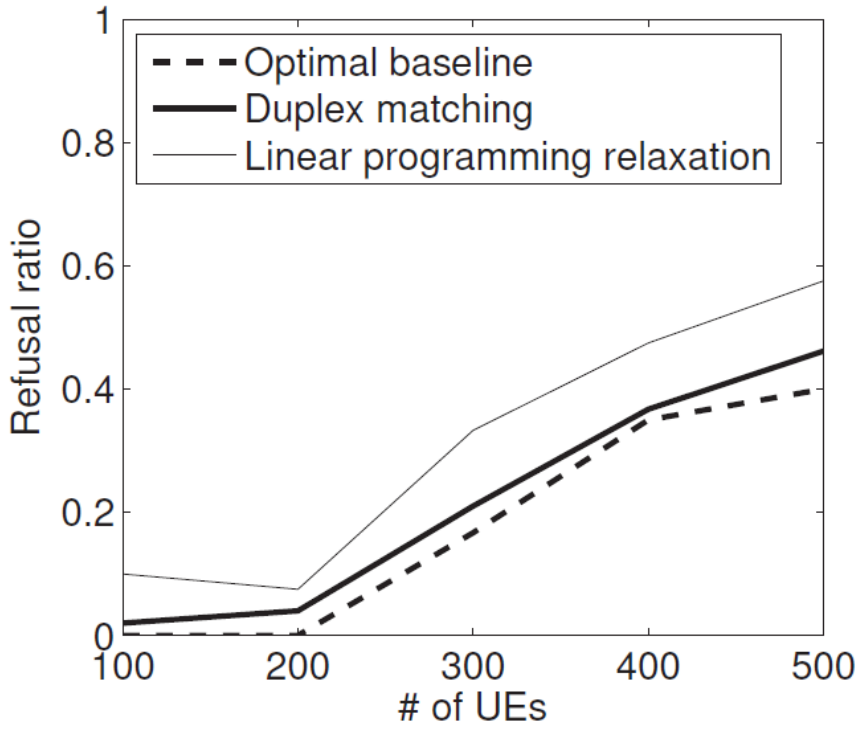
Joint Assignment

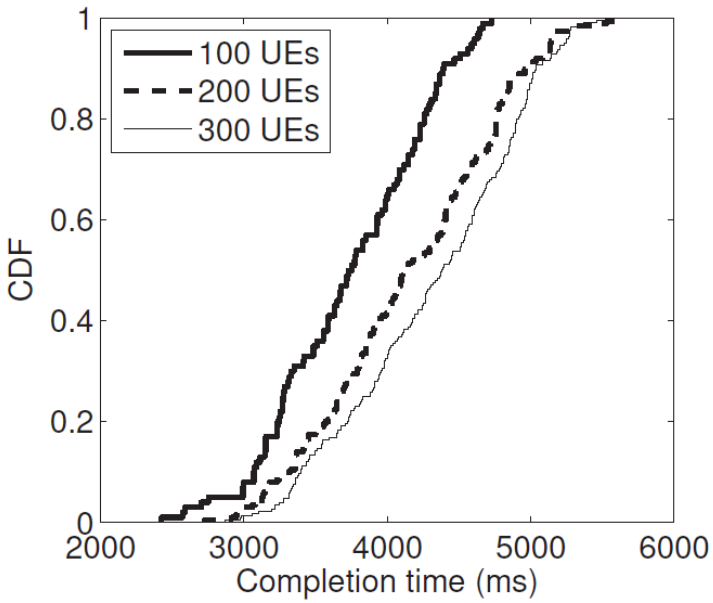
Minimize # of failures

- non-linear integer programming problem
- Matching theory

T. Li, et. Al. "On Efficient Offloading Control in Cloud Radio Access Network with Mobile Edge Computing", ICDCS 2017

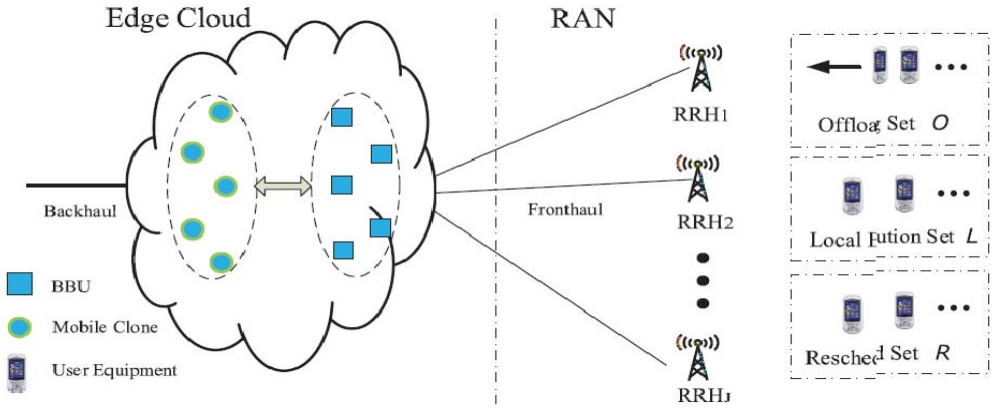

Optimal baseline
Duplex matching
Linear programming relaxation
Refusal ratio
Case #
0
0.2
0.4
0.6
0.8
1
1
2
3
4
5
6
7
8
9
10


Optimal baseline
Duplex matching
Linear programming relaxation
Refusal ratio
# of UEs
0
0.2
0.4
0.6
0.8
1
100
200
300
400
500


100 UEs
200 UEs
300 UEs
CDF
Completion time (ms)
0
0.2
0.4
0.6
0.8
1
2000
3000
4000
5000
6000

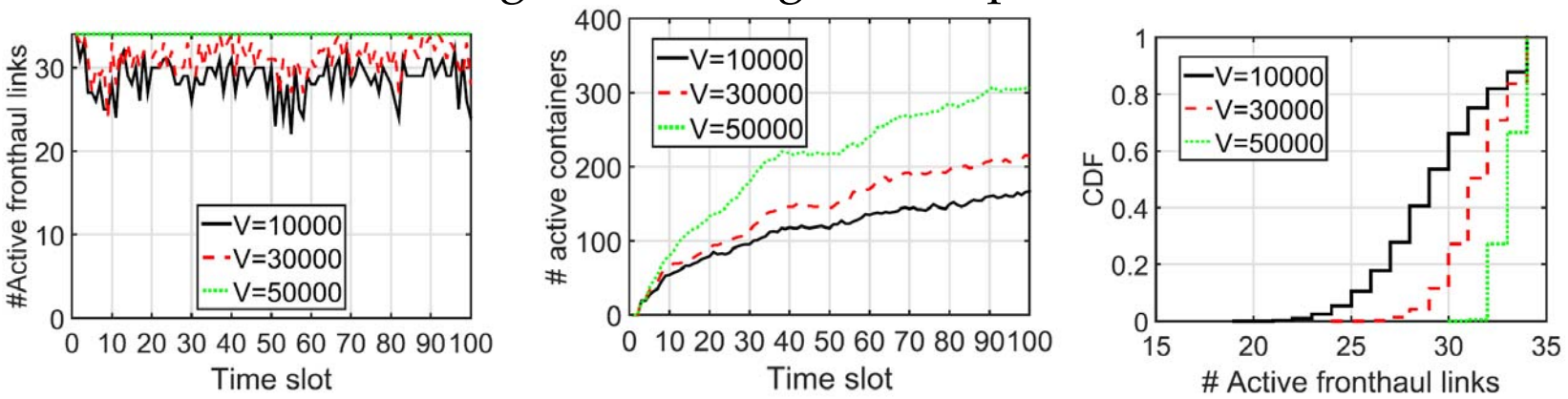
More research

- Offloading + resource allocation



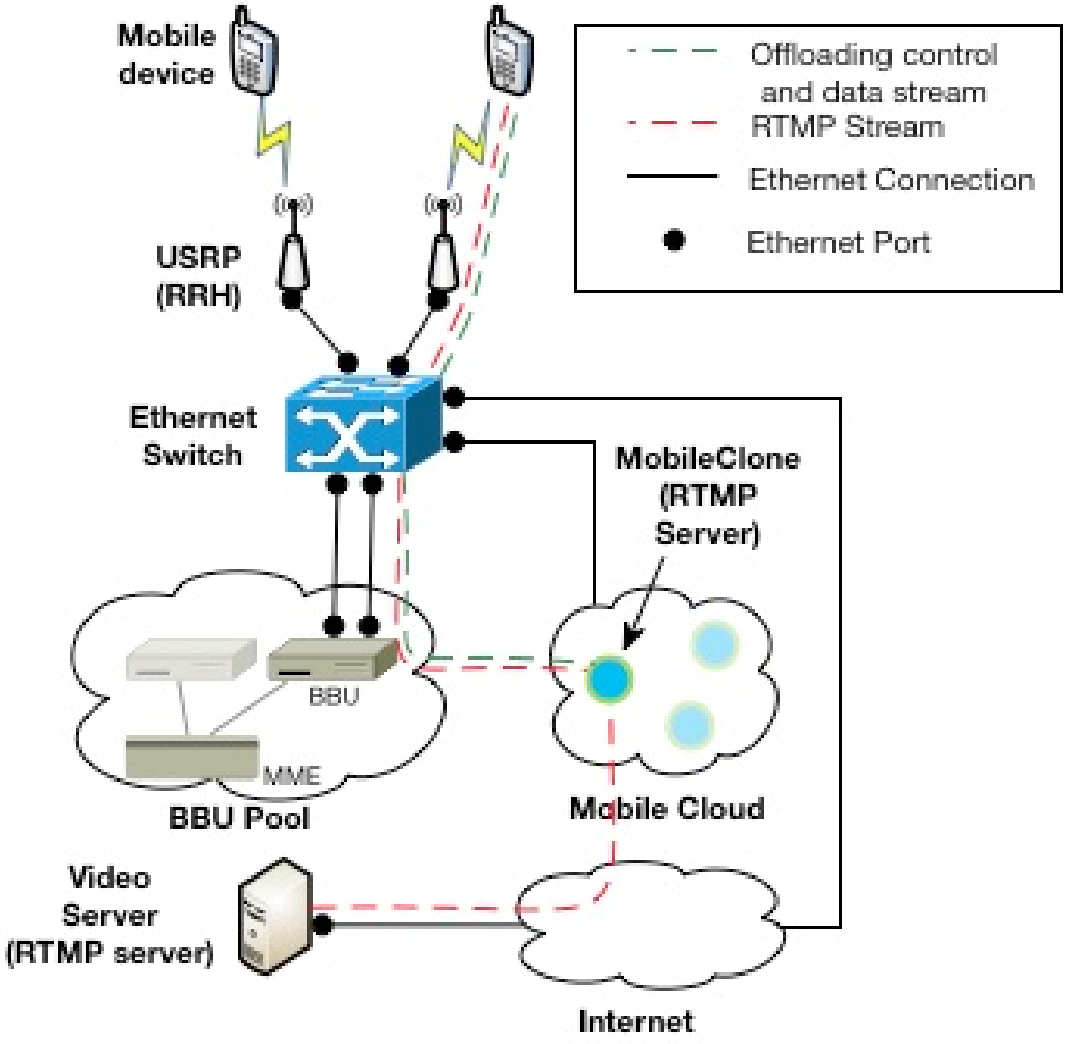
K. Wang, K. Yang, et. al. "Unified Offloading Decision Making and Resource Allocation in ME-RAN", IEEE Transactions on Vehicular Technology (TVT), Year: 2019 | Volume: 68

- Resource scheduling considering user requirement and fronthaul



X. Wang, et. al. "Dynamic Resource Scheduling in Mobile Edge Cloud with Cloud Radio Access Network", IEEE Transactions on Parallel and Distributed Systems (TPDS), Year: 2018 | Volume: 29

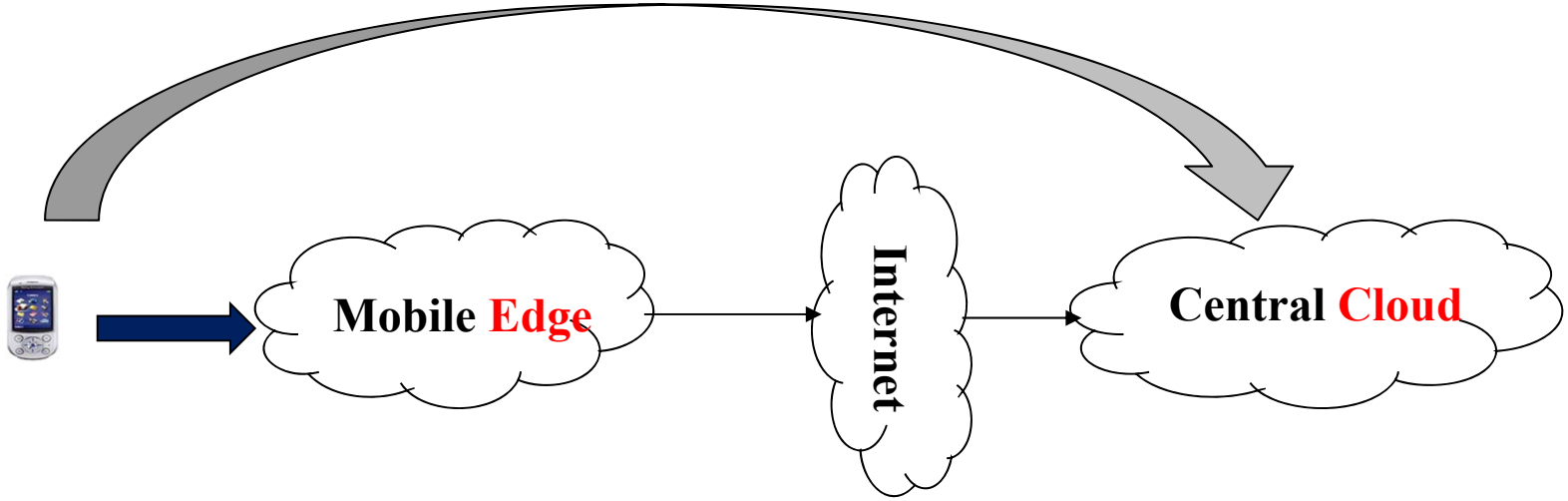
Testbed: openStack + USRPs



- Amarisoft LTE 100 software Base Station for BBUs and EPC.
  - TI/Ettus USRP N210 for Remote Radio Heads (RRH).
  - Android OS running on Mobile Devices (*Mi's RedNote*).
- *openAirInterface* in open source
  - USRP X300/X310
  - Huaiwei HDD handset
- Android x86 OS running on Clone.
- Clones are hosted on an Openstack cloud.

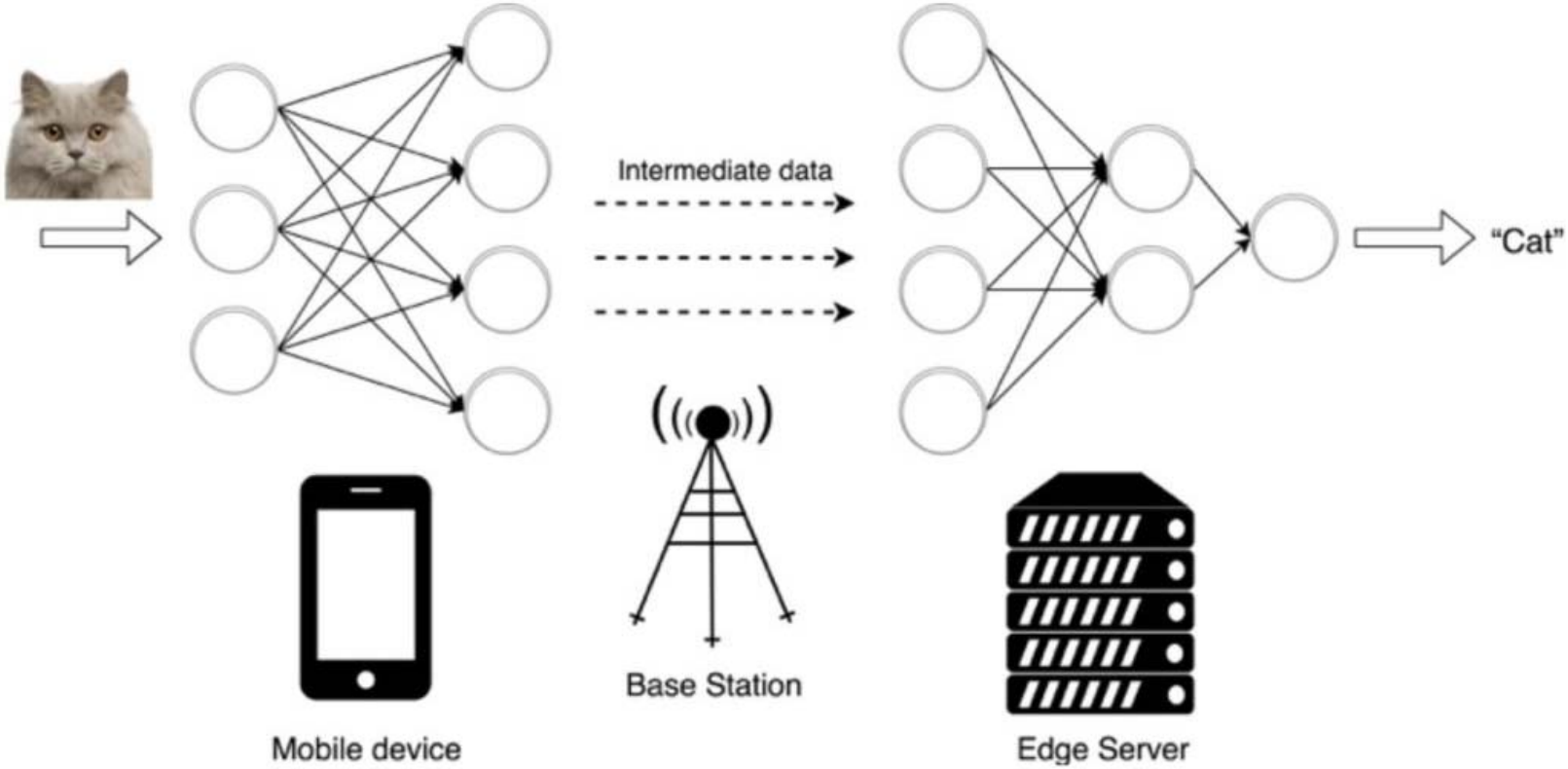
Ack: Chathura M.

Cloud-Edge Collaboration



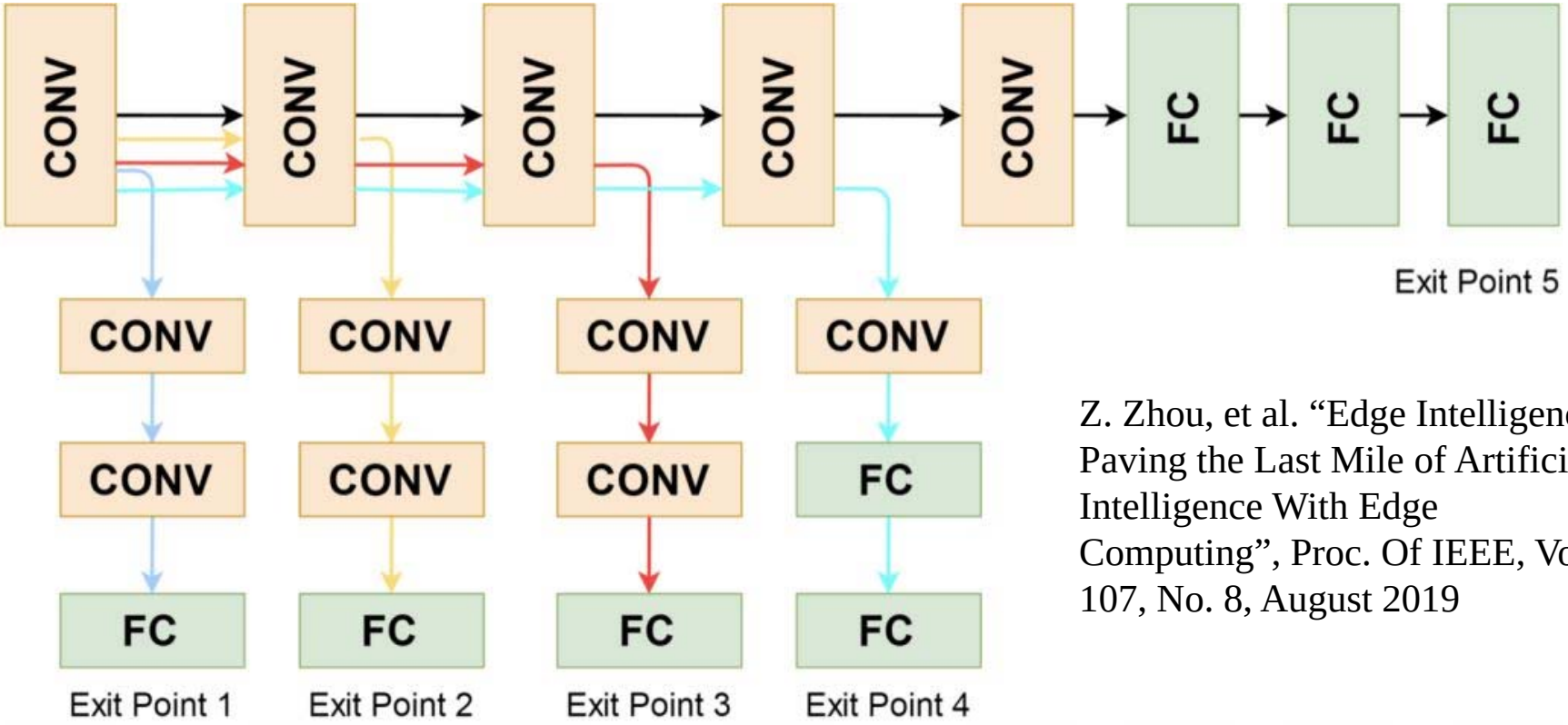
- Task offloading
- Joint resource allocation

Edge Intelligence (EI)



Key: how to simplify and distribute conventional AI algorithms/techniques, which are typically used on big servers, so as to be applicable on small edge servers

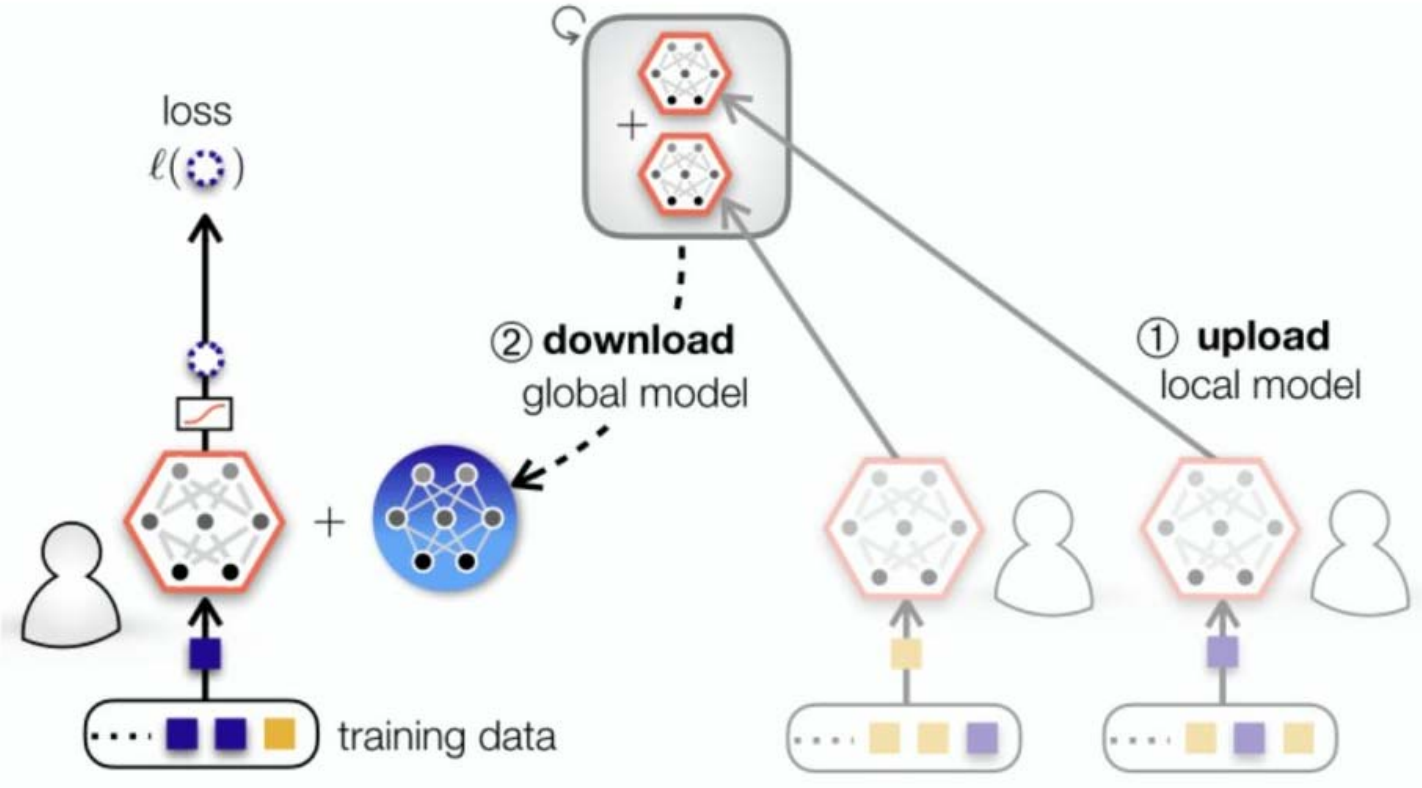
EI Technique Example #1: Early Exit



Z. Zhou, et al. "Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing", Proc. Of IEEE, Vol. 107, No. 8, August 2019

Have early exit points to end the original complex deap learning algorithms while satisfying: 1) computation and communication constraints of edge nodes; 2) task QoS (e.g., accuracy, response time)

EI Technique Example #2: Federated Learning



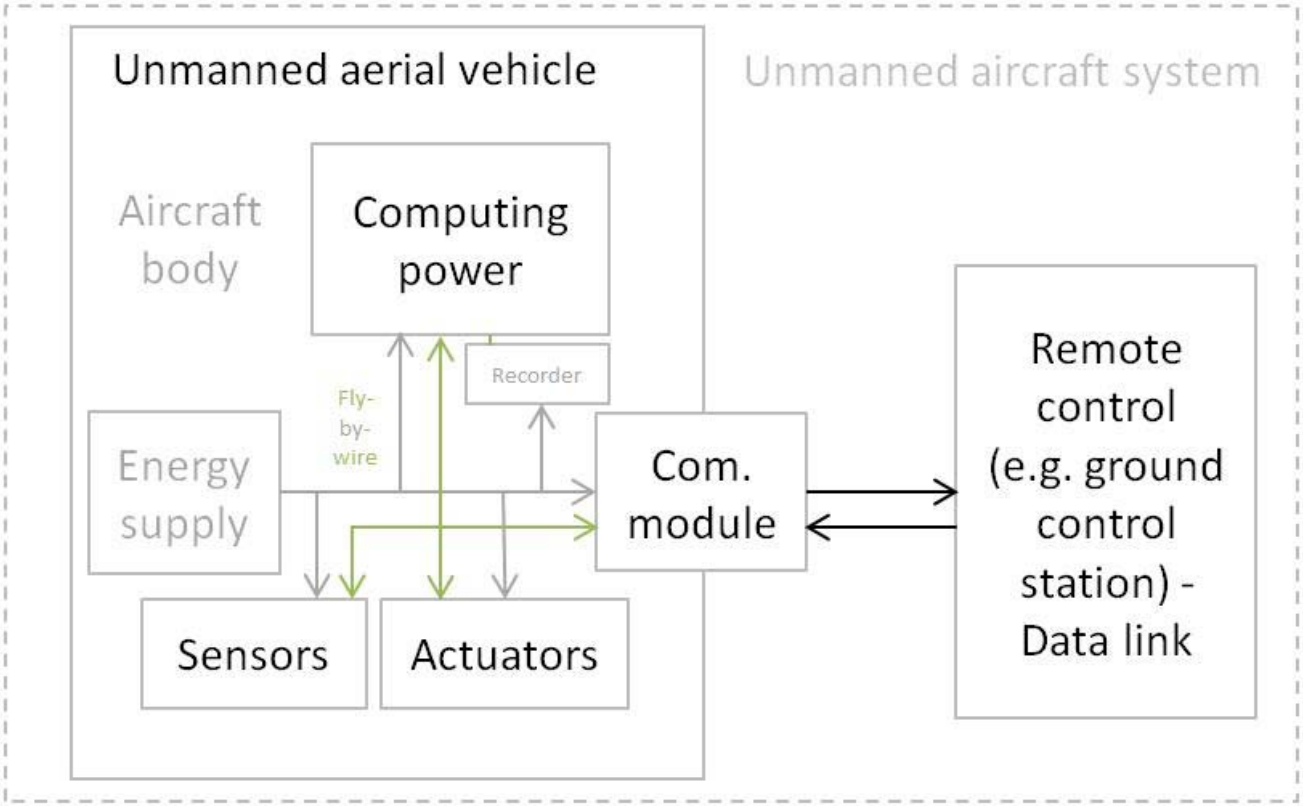
Agenda

- Mobile Edge Computing and Communications
- Unmanned Aerial Vehicles (UAV)
- MECC+UAV

- Q&A

Unmanned Aerial Vehicle

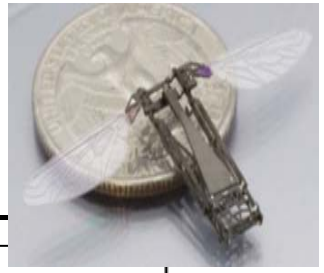
- An **unmanned aerial vehicle** (**UAV**) (commonly known as a **drone**) is an aircraft without a human pilot on board.
- Unmanned aircraft system (**UAS**): includes a **UAV**, a ground-based **controller**, and a system of **communications** between the two.



Souce: wikipedia

Physical structure of an UAV

UAV Classification: by Size



UAS Description	Weight (Pounds)	Overall Size (Feet)	Mission Altitude (Feet Above the Surface)	Mission Speed (Miles per Hour)	Mission Radius (Miles)	Mission Endurance (Hours)
Nano	< 1	<1	<400	<25	<1	<1
Micro	1 to 4.5	<3	<3,000	10 to 25	1 to 5	1
Small UAS	4.5 to 55	<10	<10,000	50 to 75	5 to 25	1 to 4
Ultralight Aircraft*	55 to 255	<30	<15,000	75 to 150	25 to 75	4 to 6
Light Sport Aircraft*	255 to 1320	<45	<18,000	75 to 150	50 to 100	6 to 12
Small Aircraft*	1,320 to 12,500	<60	<25,000	100 to 200	100 to 200	24 to 36
Medium Aircraft*	12,500 to 41,000	TBD	<100,000	TBD	TBD	TBD

Source: US Department of Transportation, “Unmanned Aircraft System (UAS) Service Demand 2015–2035: Literature Review & Projections of Future Usage,” tech. rep., v.0.1, DOT-VNTSC-DoD-13-01, Sept. 2013.

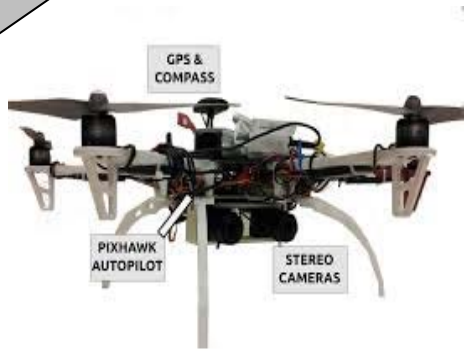
UAV Classification: By Mechanism

	Fixed-Wing	Rotary-Wing
Mechanism	Lift generated using wings with forward airspeed	Lift generated using blades revolving arounda rotor shaft
Pros	Simpler structure, usually higher payload, higher speed	Can hover, able to move in any direction, vertical takeoff and landing
Cons	Need a runway or a launcher for takeoff and landing; need to maintain forward motion	Usually lower payload, lower speed, shorter range

UAV Classification: by Degrees of Autonomy

UAV Swarm: formation and more intelligence

Remote control by a human operator

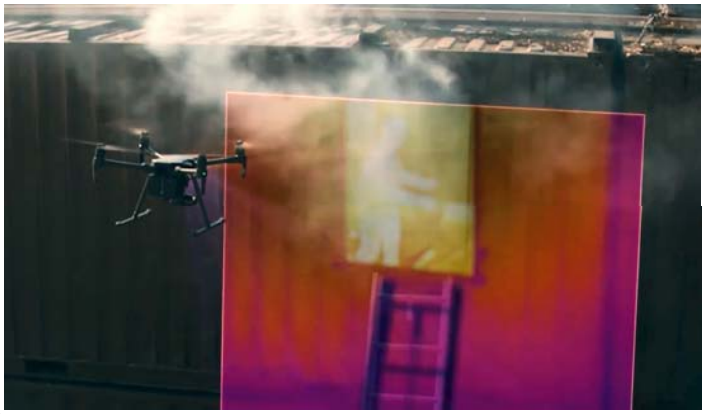


Controlled autonomously by onboard computers

UAV Classifications: By Applications

- Military uses: Reconnaissance, attack, demining, target practice,…

Filming



Public Security

Civilian Uses

Power-line Inspection

Smart Farming

Pictures are from https://www.dji.com/

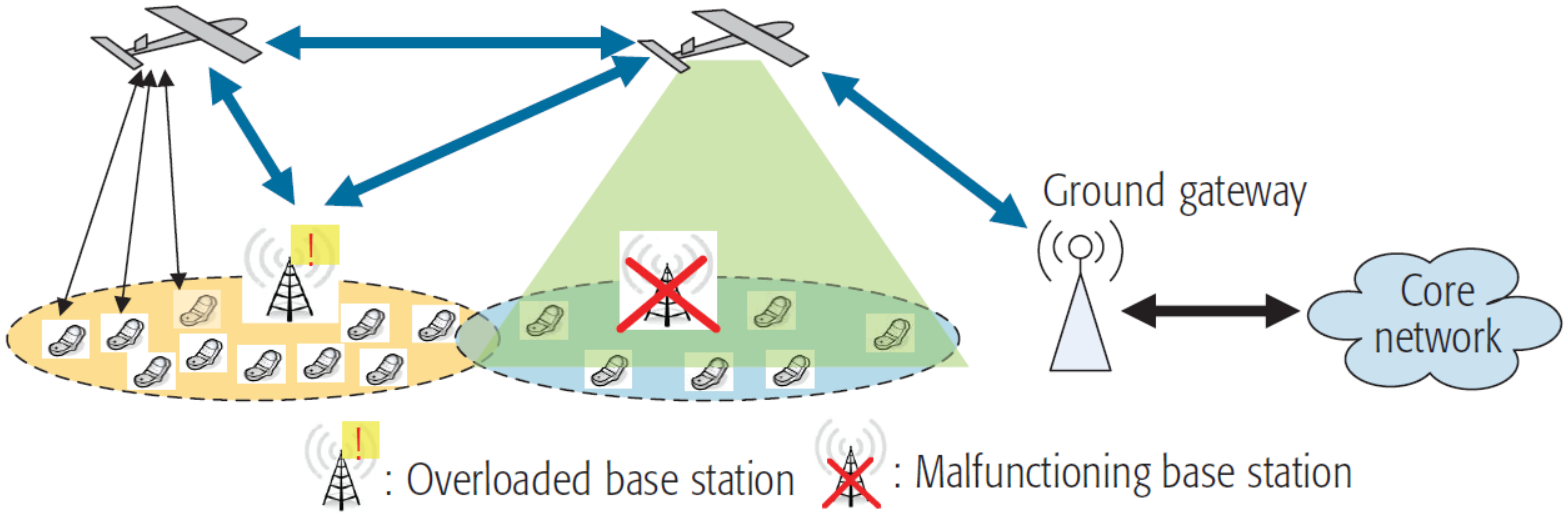
How to have my own UAVs?
To Buy or To Build?

3D-printed UAV
– U of Southampton

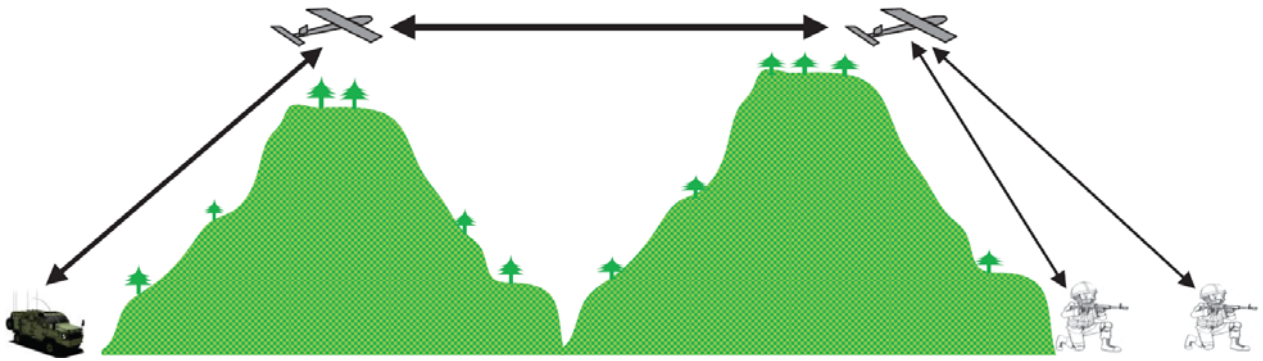
Layer	Operations	Example
Firmware	From machine code to processor execution, memory access	ArduCopter-v1, PX4
Middleware	Flight control, navigation, radio management	Cleanflight, ArduPilot
Operating system	Optic flow, obstacle avoidance, SLAM, decision-making	ROS, Nuttx, Linux distributions, Microsoft IOT

UAV-enabled Wireless Communication

UAV-aided ubiquitous coverage

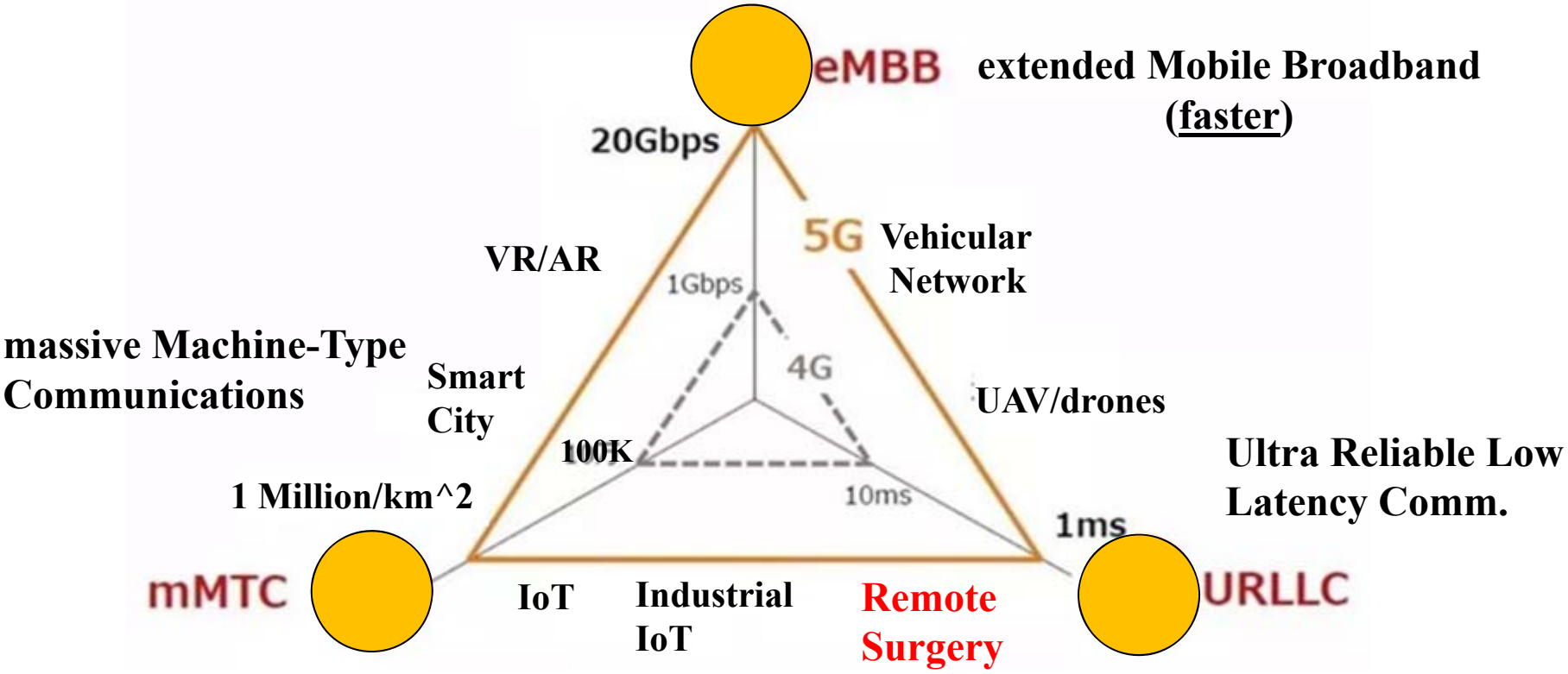


UAV-aided relaying



Y. Zeng, R. Zhang , *et al*. “Wireless communications with unmanned aerial vehicles: opportunities and challenges”. *IEEE Commun. Mag.* ,May 2016

Wireless Communications/5G for UAVs



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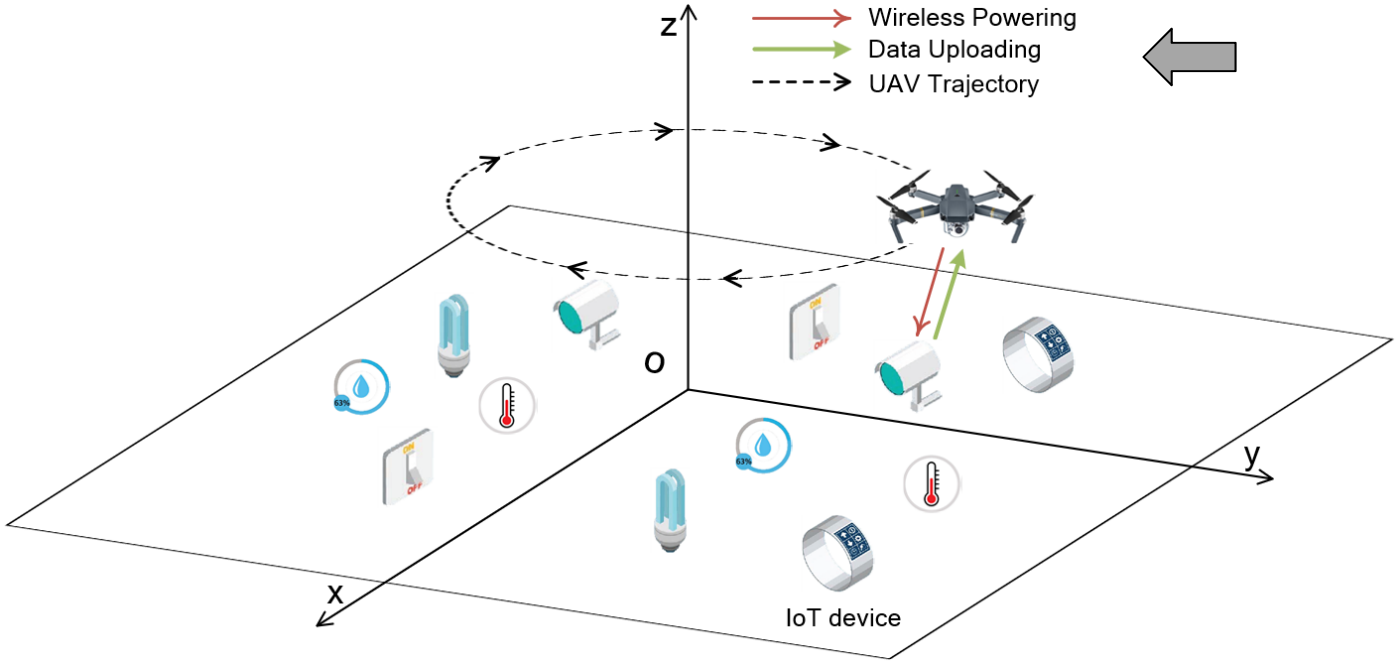
Single UAV



- A UAV moves in a constant altitude *H*, TDD communication
- UAV hovers above *N* IoT devices at *M* different locations.
- With the help of wireless powering technique, IoT devices can be charged by UAV
- **Objective**: Minimize the energy consumption of the UAV

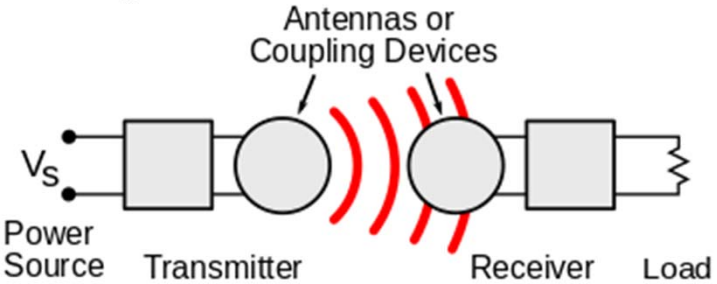
Y. Du, K. Yang, K. Wang, G. Zhang, Y. Zhao, and D. Chen, "Joint resources and workflow scheduling in UAV-enabled Wirelessly-Powered MEC for IoT systems," *IEEE Transactions on Vehicular Technology*, pp. 1–14, Aug. 2019, DOI: 10.1109/TVT.2019.2935877

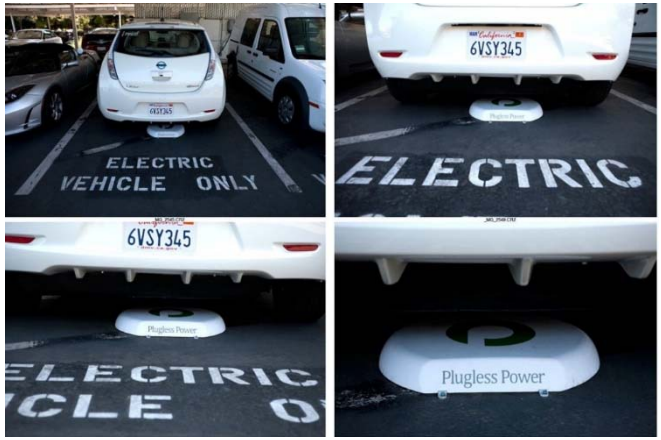
Inductive Wireless Charging (short distance)

- Smart phones run out of battery soon.

Portable Charger

Charging Pad





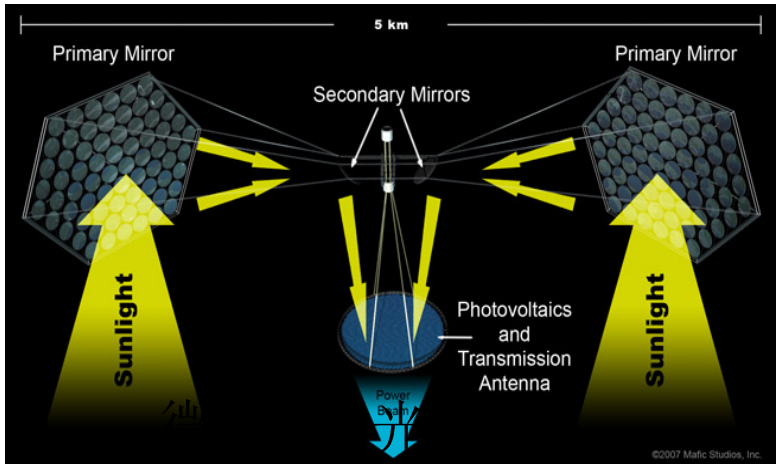
Inductive coupling

- Strict coils matching
- Short distance: mm-cm
- Frequency: Hz-MHz, suitable for small devices

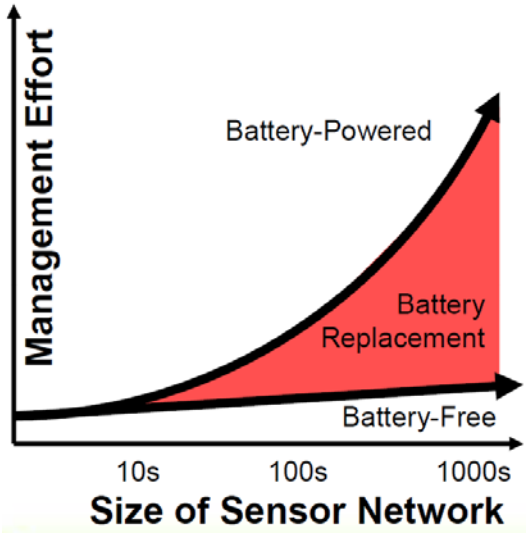
Magnetic resonant coupling

- Distance: tens of cms; not very strict coil alignment
- Frequency: KHz-MHz

Radio Frequency Wireless Charging (medium distance)



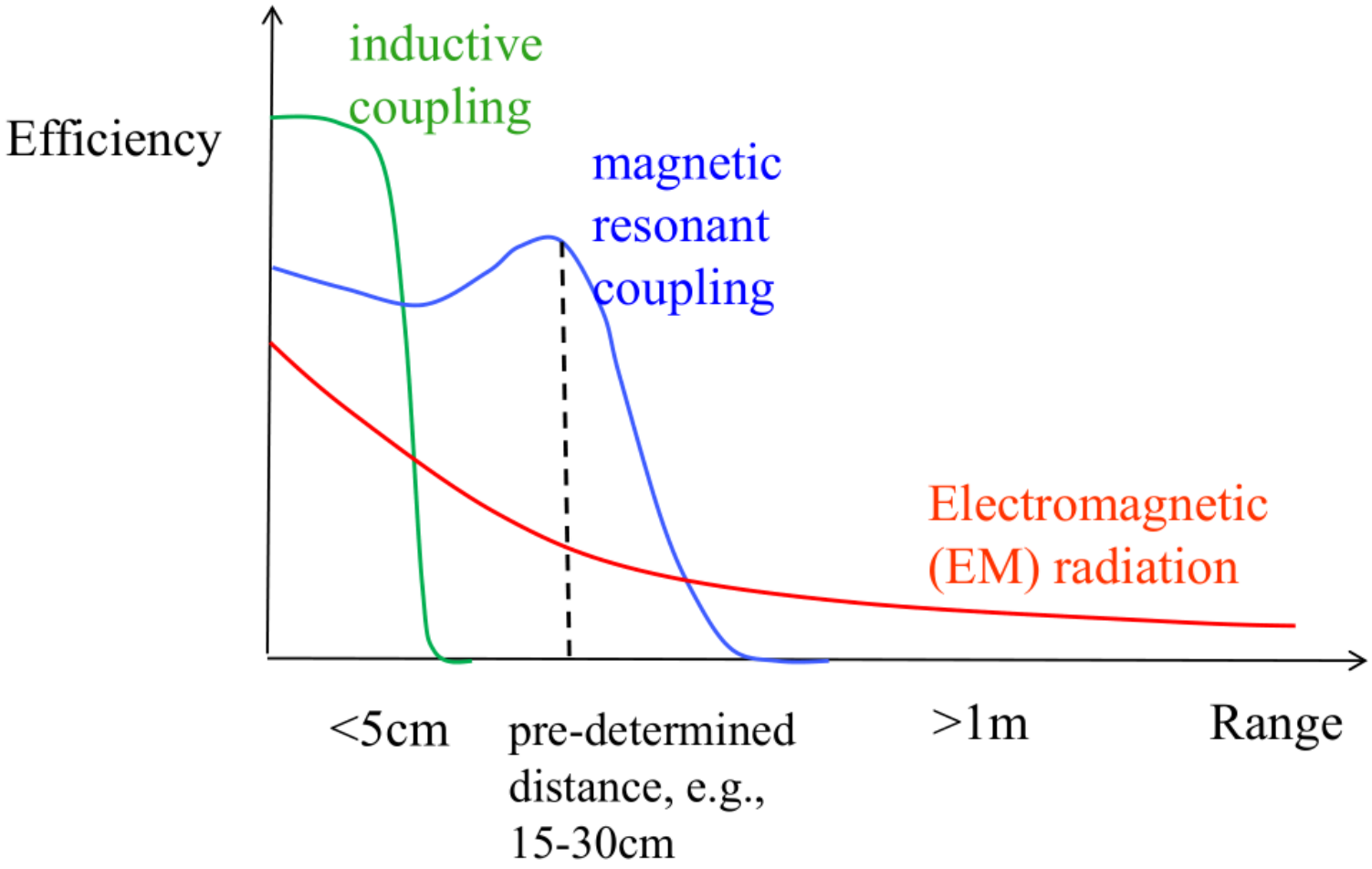
Charging IoT devices



Space solar energy to ground

Energous WattUp RF wireless charging: pushing standard 2.0, can be as far as 4.6m

Comparison



From Prof. R. Zhang's tutorial in IEEE Globecom 2016

Problem Formulation

- Channel Model : assume line of sight (LoS), perfect Doppler compensation

$$h_{ij} = \frac{h_0}{d_{ij}^2} \qquad r_{ij} = a_{ij} B \log_2 \left(1 + \frac{p_i h_{ij}}{\sigma^2}\right), \forall i \in \mathcal{N}, \forall j \in \mathcal{M}$$

- Wireless Powering Model: the harvested energy should be more than the uploading energy each IoT device consumes.

$$E_{ij}^W = v_i h_{ij} P_{uav}^W t_{ij}^w \geq p_i t_{ij}^u, \quad \forall i \in \mathcal{N}, \quad \forall j \in \mathcal{M}$$

- Computing Task Model: UAV is required to provide sufficient computing resources for each IoT device

$$\sum_{j=1}^{M} a_{ij} f_{ij} t_{ij}^c \geq F_i, \forall i \in \mathcal{N}, \forall j \in \mathcal{M}$$

Y. Du, K. Yang, K. Wang, G. Zhang, Y. Zhao, and D. Chen, "Joint resources and workflow scheduling in UAV-enabled Wirelessly-Powered MEC for IoT systems," *IEEE Transactions on Vehicular Technology*, pp. 1–14, Aug. 2019, DOI: 10.1109/TVT.2019.2935877.

Problem Formulation

$$\underset{\boldsymbol{A},\boldsymbol{F},\boldsymbol{\tau},\boldsymbol{T}}{\text{minimize}} \ \varphi(E^C + E^W) + \phi E^H$$

Minimize the energy consumption of UAV

$$\text{s.t. } a_{ij} = \{0,1\}, \quad \forall i \in \mathcal{N}, \quad \forall j \in \mathcal{M}$$

$$\sum_{j=1}^{M} a_{ij} = 1, \quad \forall i \in \mathcal{N}, \quad \forall j \in \mathcal{M}$$

IoT devices association

$$0 \le f_{ij} \le f_{max}, \quad \forall i \in \mathcal{N}, \quad \forall j \in \mathcal{M}$$

Computing capacity constants of UAV

$$v_i h_{ij} P_{uav}^W t_{ij}^w \ge p_i t_{ij}^u, \quad \forall i \in \mathcal{N}, \quad \forall j \in \mathcal{M}$$

Wireless power transfer constraints

$$a_{ij}(t_{ij}^w + t_{ij}^u + t_{ij}^c) \le t_i^{qos}, \quad \forall i \in \mathcal{N}, \quad \forall j \in \mathcal{M}$$

QoS constraints of IoT devices

$$T_j \ge \sum_{i=1}^{N} a_{ij}(t_{ij}^w + t_{ij}^u + t_{ij}^c), \quad \forall i \in \mathcal{N}, \quad \forall j \in \mathcal{M}$$

Hovering time constraints of UAV

$\boldsymbol{A}$: IoTDs association; $\boldsymbol{F}$: computing resources allocation; $\boldsymbol{\tau}$: WPT time; $\boldsymbol{T}$: UAV hovering duration

Note: UAV locations pre-defined and fixed.

Joint Resources Allocation Algorithm

Algorithm 1 The proposed iterative algorithm

1: Obtain the optimal wireless powering duration $\boldsymbol{\tau}^*$.
2: **Initialize:** $\boldsymbol{A}^0$ and let $r = 0$;
3: **Repeat:**
4: For given $\boldsymbol{A}^r$, obtain the optimal solution denoted as $\boldsymbol{F}^{r+1}$;
5: For given $\boldsymbol{F}^{r+1}$, obtain the optimal solution denoted as $\boldsymbol{A}^{r+1}$;
6: Obtain the UAV hovering durations denoted as $\boldsymbol{T}^{r+1}$;
7: Update $r = r + 1$.
8: **Until:** The fractional decrease of E is below a threshold ϵ or a maximum number of iterations ($r_{\max}$) is reached;
9: **Return:** The optimal IoTDs association $\boldsymbol{A}^*$, computing resources allocation $\boldsymbol{F}^*$, UAV wireless powering duration $\boldsymbol{\tau}^*$ and UAV hovering durations $\boldsymbol{T}^*$.

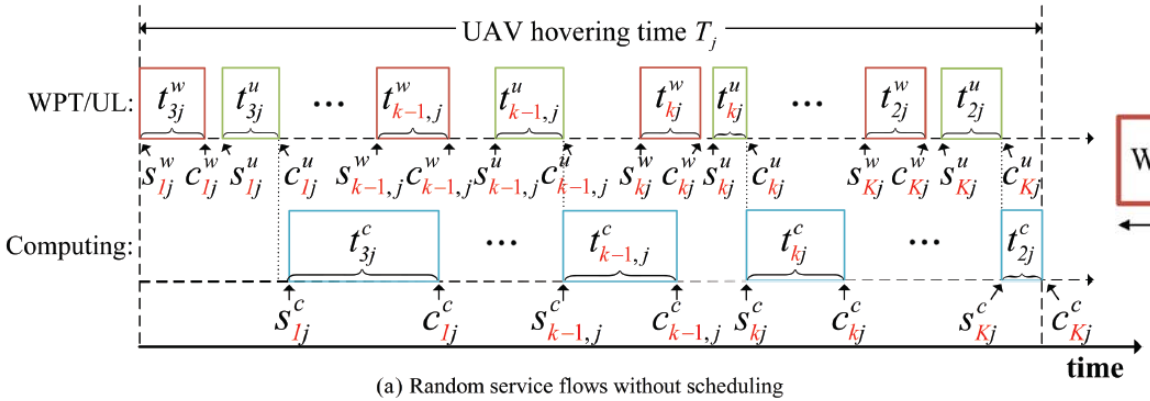
- The optimal wireless powering duration and hovering time are

$$t_{ij}^{w*} = \frac{p_i t_{ij}^u}{v_i h_{ij} P_{uav}^W}, \ \forall i \in \mathcal{N}, \ \forall j \in \mathcal{M}$$

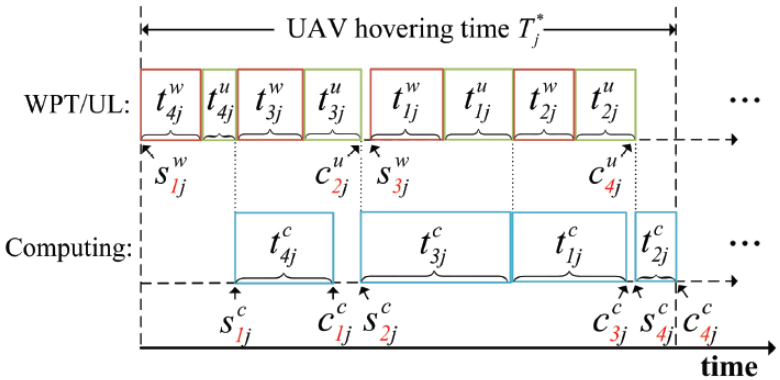
$$T_j^* = \sum_{i=1}^{N} a_{ij}(t_{ij}^w + t_{ij}^u + t_{ij}^c), \ \forall j \in \mathcal{M}$$

- The proposed iterative algorithm (i.e., block-coordinate descent method) can give a near-optimal solution to the Joint Resources Allocation problem.

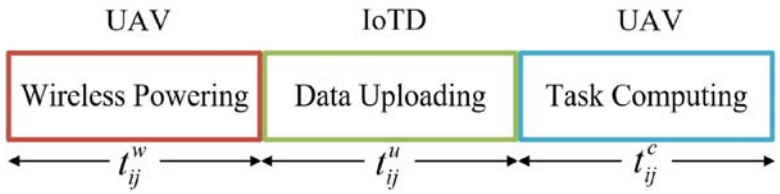
Workflow Scheduling



(a) Random service flows without scheduling



(b) Service flows after optimization



- To further minimize the hovering time of UAV, we propose the multiple-workflow structure for UAV-assisted IoT platform.
- This TDMA based workflow allows parallel transmissions and executions on different devices.
- The hovering time of UAV is minimized and the QoS of each IoTD is guaranteed at the same time.

Problem Formulation

$$\underset{\boldsymbol{A},\,\boldsymbol{F},\,\boldsymbol{\tau},\,\boldsymbol{S}}{\text{minimize}}\ \varphi(E^C + E^W) + \phi P_{uav}^H \sum_{j=1}^{M} c_{Kj}^c$$

Minimize the energy consumption of UAV

$$\text{s.t. } a_{ij}(t_{ij}^w + t_{ij}^u + t_{ij}^c) \le t_i^{qos},\ \forall i \in \mathcal{N},\ \forall j \in \mathcal{M}$$

QoS constraints of IoT devices

$$0 \le a_{ij} \le 1,\ \forall i \in \mathcal{N},\ \forall j \in \mathcal{M}$$

$$\sum_{j=1}^{M} a_{ij} = 1,\ \forall i \in \mathcal{N},\ \forall j \in \mathcal{M}$$

IoT devices association

$$0 \le f_{ij} \le f_{max},\ \forall i \in \mathcal{N},\ \forall j \in \mathcal{M}$$

Computing capacity constants of UAV

$$t_{ij}^w \ge \frac{p_i t_{ij}^u}{v_i h_{ij} P_{uav}^W},\ \forall i \in \mathcal{N},\ \forall j \in \mathcal{M}$$

Wireless power transfer constraints

$$S_j \in \mathbb{S}_j,\ \forall j \in \mathcal{M}$$

Service Sequence Constraint

$$\sum_{j=1}^{M} a_{ij} f_{ij} t_{ij}^c \ge F_i,\ \forall i \in \mathcal{N},\ \forall j \in \mathcal{M}$$

Computing Task Constraint of UAV

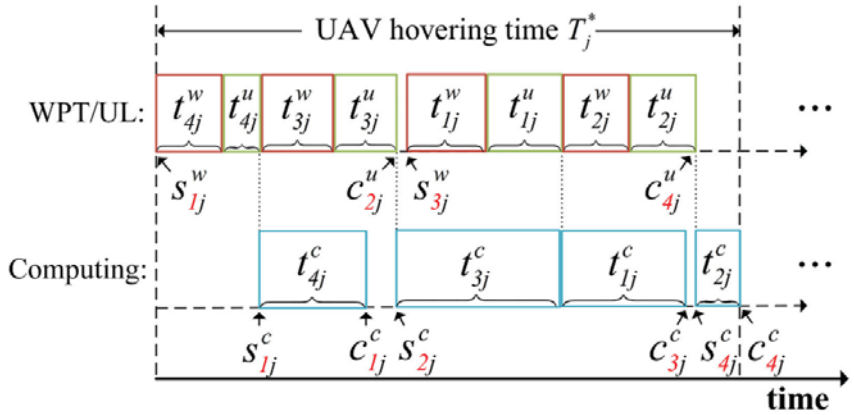
A : IoTDs association; ***F***: computing resources allocation; $\boldsymbol{\tau}$: WPT time; ***S***: service sequence of IoTDs

(c_{Kj}^c is the last computing task completion time in each *j*-th hovering place).

Hovering Time Minimization Algorithm

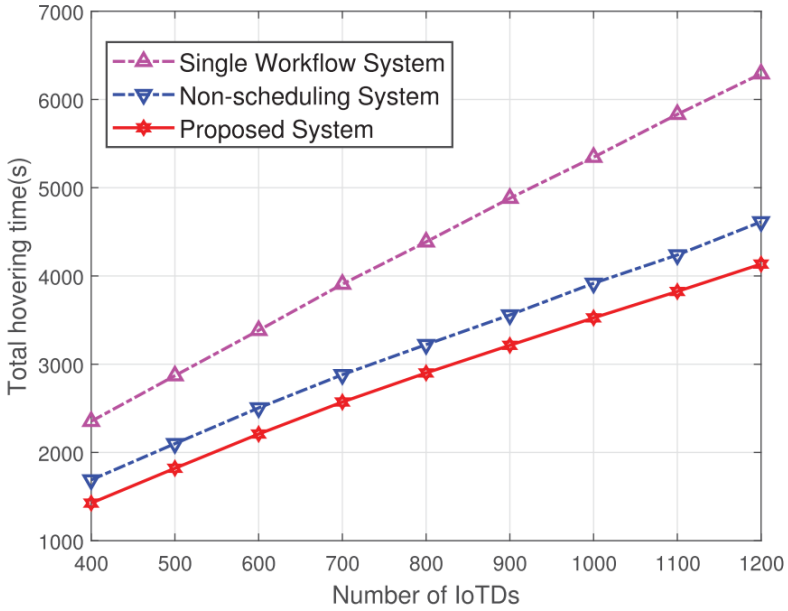
Algorithm 3 Optimal UAV hovering time minimization algorithm

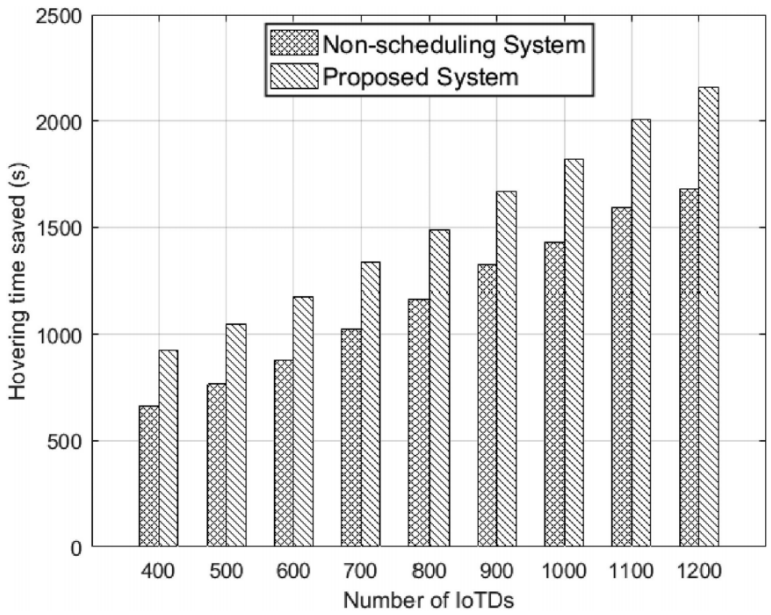
Given the optimal t_{ij}^{u*}, t_{ij}^{c*} and t_{ij}^{w*}, let $n = 0$, $m = 0$;
Repeat:
Find the minimal time $t_{k_{min}}$ in time sets $\boldsymbol{T_1}$ and $\boldsymbol{T_2}$;
If $t_{k_{min}} \in \boldsymbol{T_1}$ then $S_{n+1} = k_{min}$, $n = n + 1$;
else if $t_{k_{min}} \in \boldsymbol{T_2}$ then $S_{K-m} = k_{min}$, $m = m + 1$;
Remove $t_{k_{min}}^{tf}$ from $\boldsymbol{T_1}$ and $t_{k_{min}}^{c}$ from $\boldsymbol{T_2}$;
Until: $\boldsymbol{T_1}$ and $\boldsymbol{T_2} = \varnothing$;
Update n=1 and $s_1^{tf} = 0$;
Repeat:
If $t_{n+1}^{tf} \geq t_n^c$ then $c_{n+1}^c = s_n^{tf} + t_n^{tf} + t_{n+1}^{tf} + t_{n+1}^c$ and $s_{n+1}^{tf} = s_n^{tf} + t_n^{tf}$;
If $t_{n+1}^{tf} < t_n^c$ then $c_{n+1}^c = s_n^{tf} + t_n^{tf} + t_n^c + t_{n+1}^c$ and $s_{n+1}^{tf} = s_n^{tf} + t_n^{tf} + t_n^c - t_{n+1}^{tf}$;
$n = n + 1$;
Until: $n = K$;
$T_j^* = c_{Kj}^c$;
Return: The optimal services sequence $\boldsymbol{S}^*$ and the optimal UAV hovering durations $\boldsymbol{t}^*$ for $\mathcal{P}1$.



- The two-stage flow-shop problem can be solved by Johnson's algorithm.
- Based on the traditional Johnson's algorithm, we develop the novel hovering time minimization algorithm.

Hovering Time Minimization





- Even if the multi-workflow system is not scheduled, the hovering time of UAV is significantly reduced compared with single workflow system.

Joint Workflow + Resources Allocation

Algorithm 4 The proposed iterative algorithm for multi-workflow system

1: **Initialize:** $\boldsymbol{A}^0$ and $\boldsymbol{S}^0$. Let $r = 0$.
2: **Repeat:**
3: For given $\{\boldsymbol{A}^r, \boldsymbol{S}^r\}$, obtain the optimal solution denoted as $\boldsymbol{F}^{r+1}$;
4: For given $\{\boldsymbol{S}^r, \boldsymbol{F}^{r+1}\}$, obtain the optimal solution denoted as $\boldsymbol{A}^{r+1}$;
5: For given $\{\boldsymbol{A}^{r+1}, \boldsymbol{F}^{r+1}\}$, use Algorithm 3 to obtain the optimal solution denoted as $\boldsymbol{S}^{r+1}$ and $\boldsymbol{T}^{r+1}$;
6: Update $r = r + 1$.
7: **Until:** The fractional decrease of E is below a threshold ϵ or a maximum number of iterations ($r_{\max}$) is reached;
8: **Return:** The optimal IoTDs association $\boldsymbol{A}^*$, computing resources allocation $\boldsymbol{F}^*$, UAV hovering durations $\boldsymbol{T}^*$ and the services sequence of the IoTDs $\boldsymbol{S}^*$.

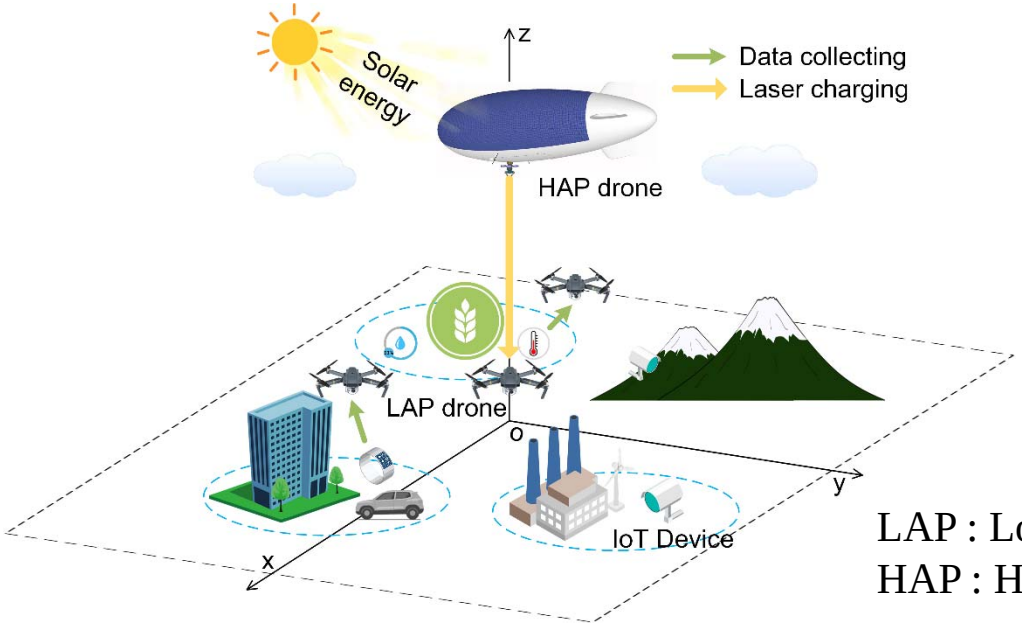
- The optimal wireless powering duration and hovering time are

$$t_{ij}^{w*} = \frac{p_i t_{ij}^u}{v_i h_{ij} P_{uav}^W}, \ \forall i \in \mathcal{N}, \ \forall j \in \mathcal{M}$$

$$T_j^* = c_{Kj}^{c*}, \ \forall j \in \mathcal{M}$$

- The proposed iterative algorithm (i.e., block-coordinate descent method) can give a near-optimal solution to the Joint Resources Allocation problem.

Multiple UAVs



LAP : Low Altitude Platform
HAP : High Altitude Platform

- Two kinds of drones: the LAPs (UAVs) and a solar-powered HAP serving as energy charging stations for all the LAPs
- *M* LAPs hovers above *K* Desired Regions (DRs). For example, the DRs in smart cities may include remote factories, farms and crowded buildings, etc.

- Objective: Minimize the energy consumption of the system

Y. Du, K. Wang, K. Yang, and G. Zhang, "Trajectory design of Laser-Powered Multi-Drone enabled data collection system for smart cities," *in 2019 IEEE Global Communications Conference (GLOBECOM)*, Dec. 2019,.

Problem Formulation

- UAVs mobility constraints:

$$q_j[S_j] = q_j[0], \forall j \in \mathcal{M}$$
$$\sum_{j=1}^{M} \sum_{t=1}^{S_j} a_j^k[t] = 1, \forall j \in \mathcal{M}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T}_j$$
$$d_j[t] = \|q_j[t] - q_j[t-1]\|, \forall t \in \mathcal{T}_j, \forall j \in \mathcal{M}$$
$$\mathcal{T}_j = \{1, 2, ..., S_j\}, \forall j \in \mathcal{M}$$

$q_j[0]$: initial location of *j*-th UAV

$q_j[S_j]$: final location of *j*-th UAV

$d_j[t]$: distance between two destinations (significantly affected by the order *t*)

- Laser Powering Model: The laser energy that each LAP receives from the HAP should be enough for its flight

$$\eta_j = \frac{P_j^r}{P_j^l} = e^{-\alpha_j(H-h)} \qquad \eta_j P_j^l \tau_j \geq E_j, \forall j \in \mathcal{M}$$

Problem Formulation

$$\mathcal{P}1: \underset{\boldsymbol{A},\, \boldsymbol{S},\, \boldsymbol{Q},\, \boldsymbol{\tau}}{\text{minimize}} \sum_{j=1}^{M} \eta_j P_j^l \tau_j$$

Minimize energy consumption of system/HAP

$$\text{s.t. } E_j \leq C_j,\ \forall j \in \mathcal{M}$$

UAV battery capacity as powered by laser

$$\eta_j P_j^l \tau_j \geq E_j,\ \forall j \in \mathcal{M}$$

Laser charging constraints

$$q_j[S_j] = q_j[0],\ \forall j \in \mathcal{M}$$

$$\sum_{j=1}^{M} \sum_{t=1}^{S_j} a_j^k[t] = 1,\ \forall j \in \mathcal{M},\ \forall k \in \mathcal{K},\ \forall t \in \mathcal{T}_j$$

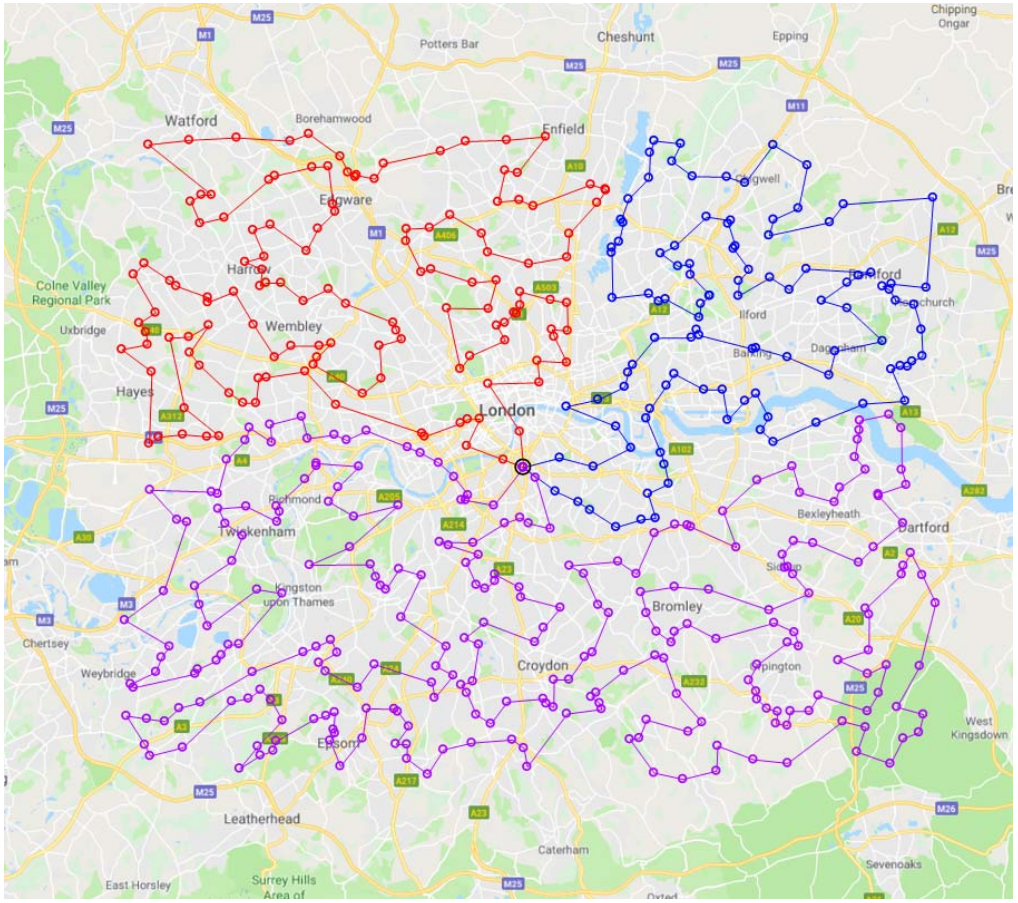
$$d_j[t] = \|q_j[t] - q_j[t-1]\|,\ \forall t \in \mathcal{T}_j,\ \forall j \in \mathcal{M}$$

$$\mathcal{T}_j = \{1, 2, ..., S_j\},\ \forall j \in \mathcal{M}$$

UAVs trajectory constraints

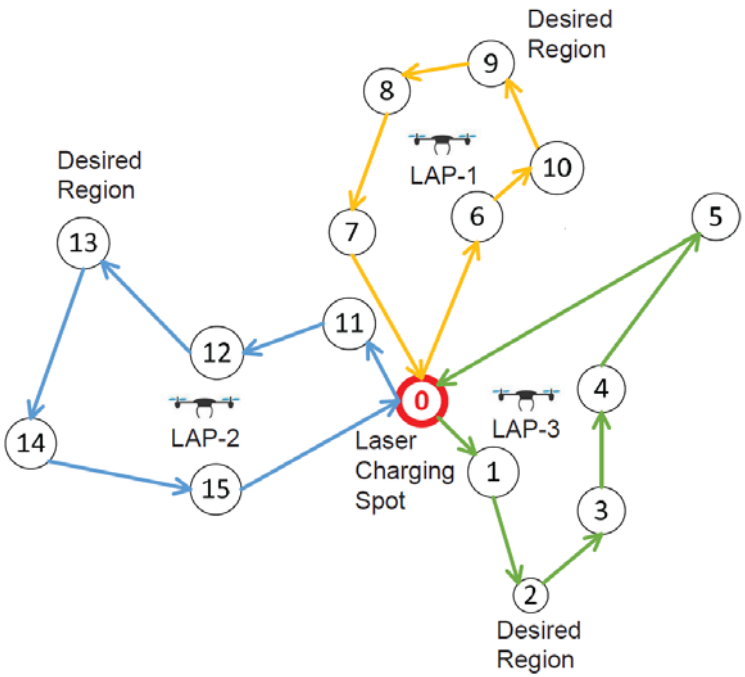
$\boldsymbol{A}$: selection of DRs; $\boldsymbol{S}$: the number of DRs seleted by each LAP;
$\boldsymbol{\tau}$: Laser charging duration; $\boldsymbol{Q}$: multi-LAP routes.

Trajectory Design



An Example of Trajectory Design for London

Drones Traveling Problem



- The trajectory design problem is a typical one deposit multiple traveling salesmen problem (TSP) with the time window. We rename it as Drones Traveling Problem (DTP).
- Our proposed DTA only uses 5 iterations (fast convergence) to obtain the near-optimal solution whereas the normal Genetic Algorithm needs nearly 10000 iterations and still fails to obtain an acceptable solution.

Drones Traveling Algorithm

- Solving DTP is equivalent to obtaining the optimal direct graph $\boldsymbol{s}*$;
- We define the local optimum graph as the graph with no self-knot in each LAP cycle;
- We use the efficient and effective 2-opt algorithm to transform a graph into a local optimum graph;
- We develop an efficient method to jump from the local optimum graph to a better graph. The Jump operations include three simple operations: the Exchanging, Shifting and the Knot Removing.

Drones Traveling Algorithm

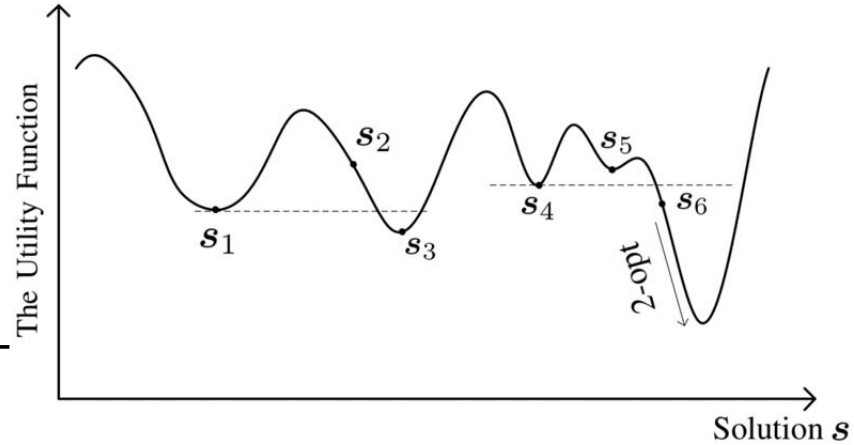
Algorithm 1: The Drones Traveling Algorithm (DTA) for $\mathcal{P}1$

Input: $\boldsymbol{A}^0$, $\boldsymbol{Q}^0$, $\boldsymbol{S}^0$: Random Solutions
Output: $\boldsymbol{A}^*$, $\boldsymbol{Q}^*$, $\boldsymbol{S}^*, \boldsymbol{\tau}^*$: The Near-optimal Solutions

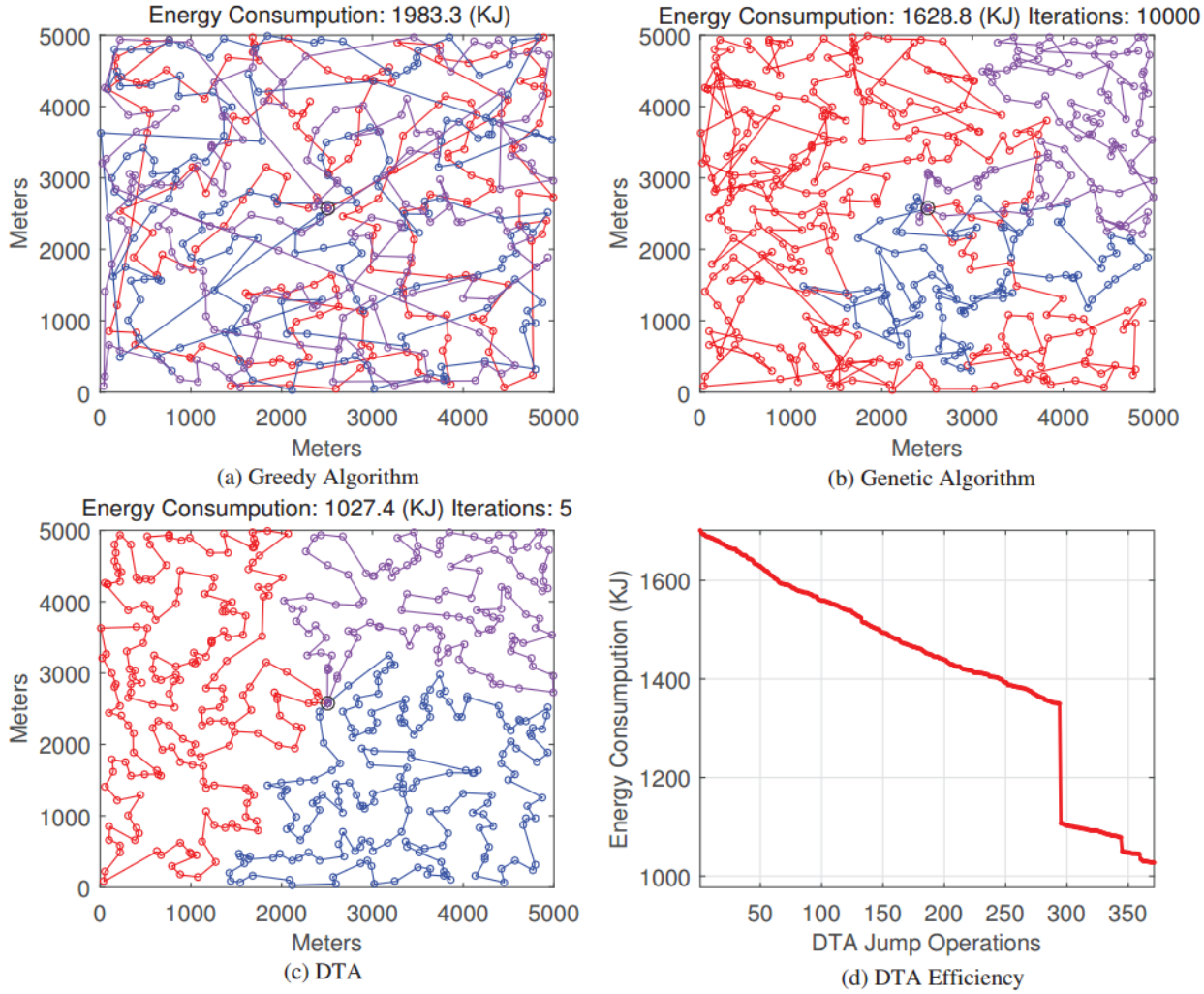
$r \leftarrow 1$; // the iterations of DTA
Generate a direct graph $\boldsymbol{s}^r$ using $\boldsymbol{A}^0$, $\boldsymbol{Q}^0$, $\boldsymbol{S}^0$;
$f(\boldsymbol{s}^0) \leftarrow \infty$; // initialize the utility function
while $f(\boldsymbol{s}^r) < f(\boldsymbol{s}^{r-1})$ **do**
  Use the *2-opt algorithm* to obtain the local optiaml direct graph $\boldsymbol{s}^r$;
  Jump from graph $\boldsymbol{s}^r$ to a new direct graph $\boldsymbol{s}^{r+1}$;
  $r \leftarrow r + 1$;
end
Use direct graph $\boldsymbol{s}^r$ to obtain $\boldsymbol{A}^*$, $\boldsymbol{Q}^*$, $\boldsymbol{S}^*$;
Obtain the optimal $\boldsymbol{\tau}^*$;
return: $\boldsymbol{A}^*$, $\boldsymbol{Q}^*, \boldsymbol{S}^*, \boldsymbol{\tau}^*$.

- The utility function *f*(**s**) is the system energy consumption (UAV energy consumption):

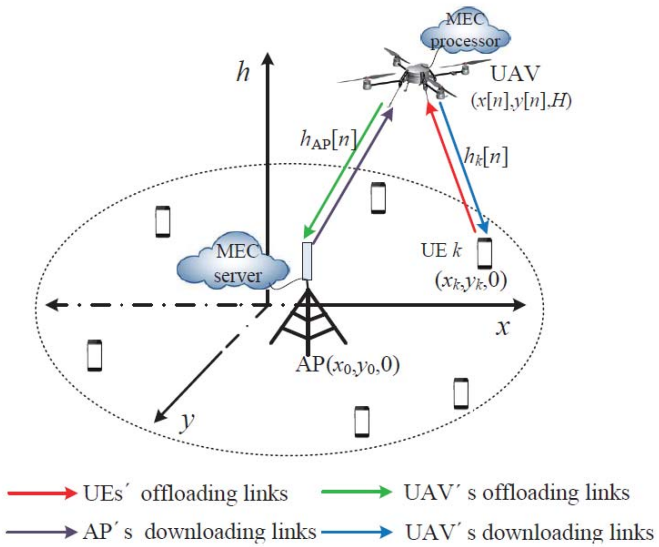
$$\sum_{j=1}^{M}\sum_{k=1}^{K}\sum_{t=1}^{S_j} P^H a_j^k[t]T^k + \sum_{j=1}^{M}\sum_{t=1}^{S_j} P^F d_j[t]v^{-1}$$



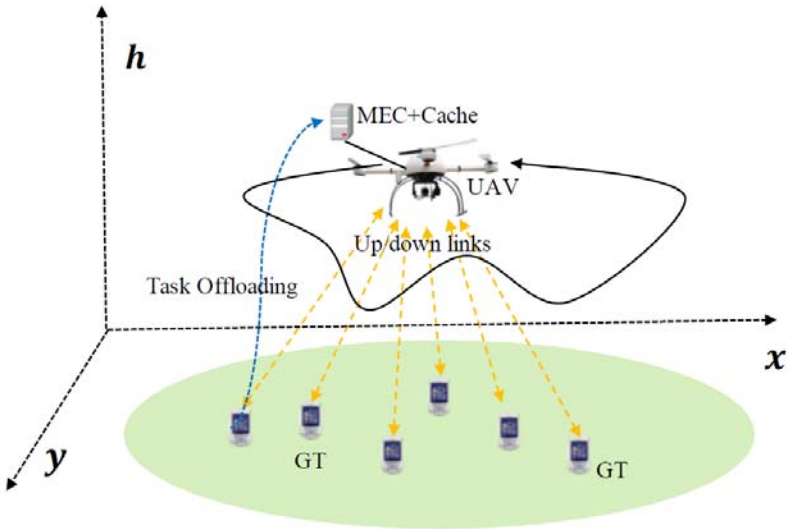
Trajectory Design



More Research



X. Hu, et al. "UAV-Assisted Relaying and Edge Computing: Scheduling and Trajectory Optimization", IEEE Trans. On Wireless Comm (TWC), 2019



- 3D+caching

H. Mei, et al. "Joint Trajectory-Resource Optimization in UAV-enabled Edge-Cloud System with Virtualized Mobile Clone", IEEE Journal of IoT, 2019

The Internet-Above-the-Clouds

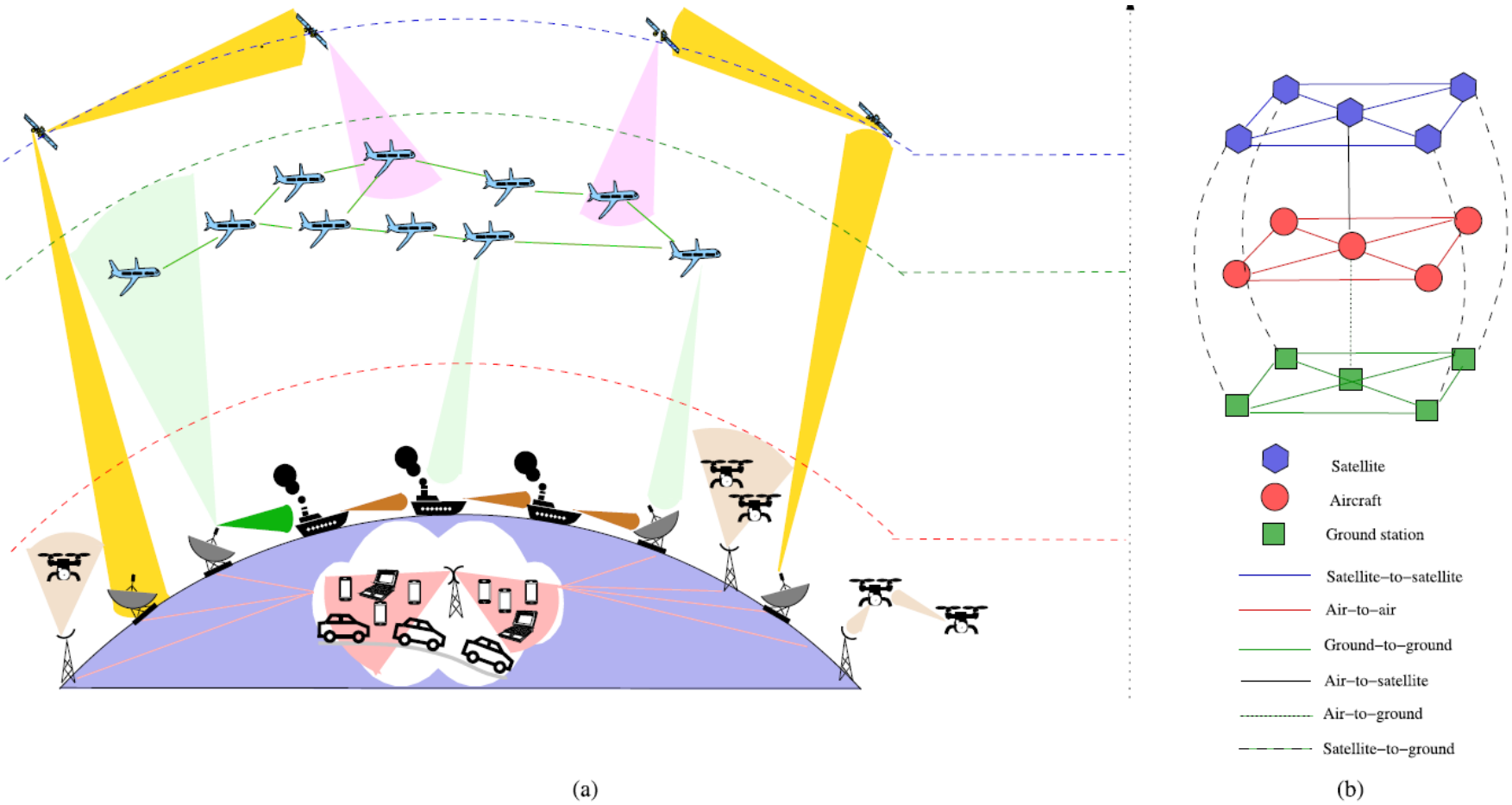
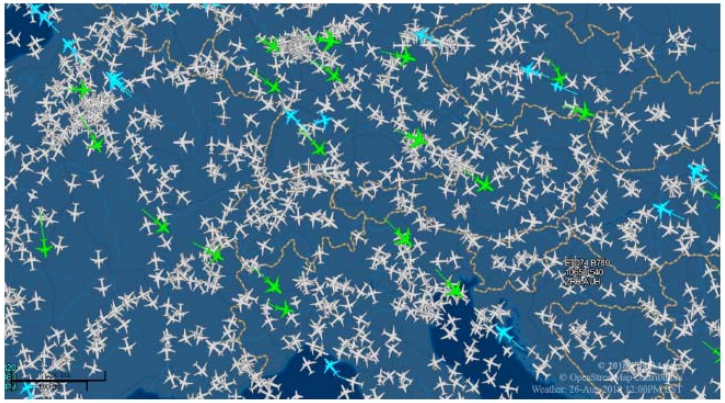


Fig. 1. ***AANET topology and the corresponding logical topology. (a) PHY topology. (b) Logical topology.***

Zhang *et al.*: "AANET for the Internet-Above-the-Clouds", Proceedings of IEEE, *Vol. 107, No. 5, May 2019*

Using Aircrafts as Base Stations?

(a) Heathrow airport



(b) European airspace

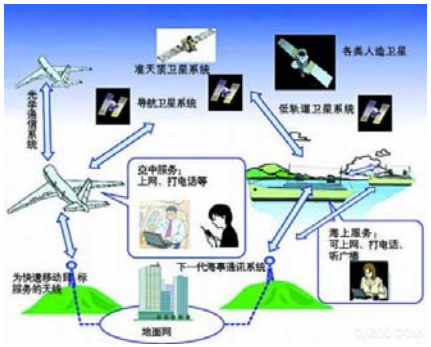
(c) North Atlantic

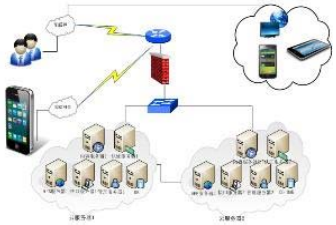
Aircraft mobility patterns

Zhang *et al.*: "AANET for the Internet-Above-the-Clouds", Proceedings of IEEE, *Vol. 107, No. 5, May 2019*

Future Air-Ground-Sea Integrated Networks

Air-Ground-Sea Integrated Networks





Mobile Internet

Internet of Things (IoT)

Mobile Communications

Marconi Wireless Communication

Signal Beacon

Smoke Signal

We have a long way to go ...

About 80% of the land and 95% of the sea in the world still has no wireless connections!

Summary

- Close collaboration between communication and computing is necessary
- UAV/aircraft-enabled mobile edge computing and communications are promising

Thanks for your attention!