Intelligent Massive NOMA towards 6G: Signal Processing Advances and Emerging Applications

Dr. Yuanwei Liu

Queen Mary University of London, UK

yuanwei.liu@qmul.ac.uk

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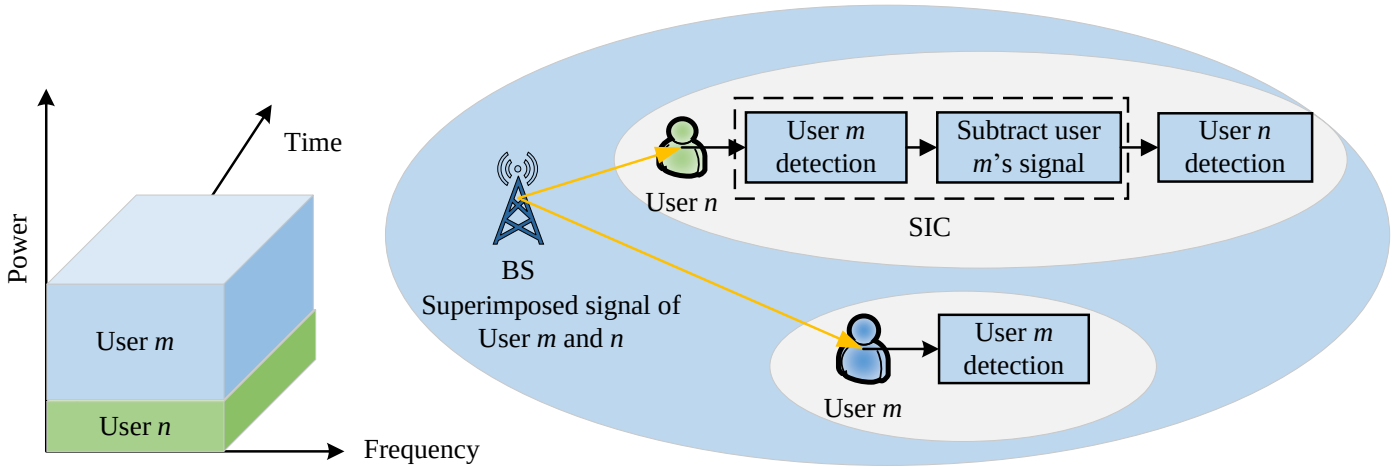
Outline

From OMA to NOMA

1. **Question**: What is multiple access?
2. **Orthogonal multiple access (OMA)**: e.g., FDMA, TDMA, CDMA, OFDMA.
3. New requirements in beyond 5G
   - Ultra-high spectrum efficiency.
   - Massive connectivity.
   - Heterogeneous QoS and mobility requirement.
4. **Non-orthogonal multiple access (NOMA)**: to break orthogonality.
5. Standard and industry developments on NOMA
   - **Whitepapers**: DOCOMO, METIS, NGMN, ZTE, SK Telecom, etc.
   - **LTE Release 13**: a two-user downlink special case of NOMA.
   - **Next generation digital TV standard ATSC 3.0**: a variation of NOMA, termed Layer Division Multiplexing (LDM).

Power-Domain NOMA Basics



1. Supports multiple access within a given resource block (time/frequecy/code), using **different power levels** for distinguishing/separating them [1].
2. Apply successive interference cancellation (SIC) at the receiver for separating the NOMA users [2].
3. If their power is similar, PIC is a better alternative.

[1] **Y. Liu** *et al.*, "Non-Orthogonal Multiple Access for 5G", ***Proceedings of the IEEE***; Dec 2017. (**Web of Science Hot paper**)

[2] Z. Ding, Y. Liu, *et al.* (2017), "Application of Non-orthogonal Multiple Access in LTE and 5G Networks", ***IEEE Communication Magazine***;(**Web of Science Hot paper**).

Power NOMA Basics

1. **Question**: Why NOMA is a popular proposition for beyond 5G?
2. Consider the following two scenarios.
   - If a user has poor channel conditions
     - The bandwidth allocated to this user via OMA cannot be used at a high rate.
     - NOMA - **improves the bandwidth-efficiency**.
   - Do not only need to pay attention to 5G and beyond
   - If the use of OMA does not fulfill the requirements of users
   - NOMA - serves more than one user in the same resource

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   - If a user only needs a low data rate, e.g. IoT networks.
     - The use of OMA gives the IoT node more capacity than it needs.
     - NOMA - **heterogeneous QoS** and **massive connectivity**.

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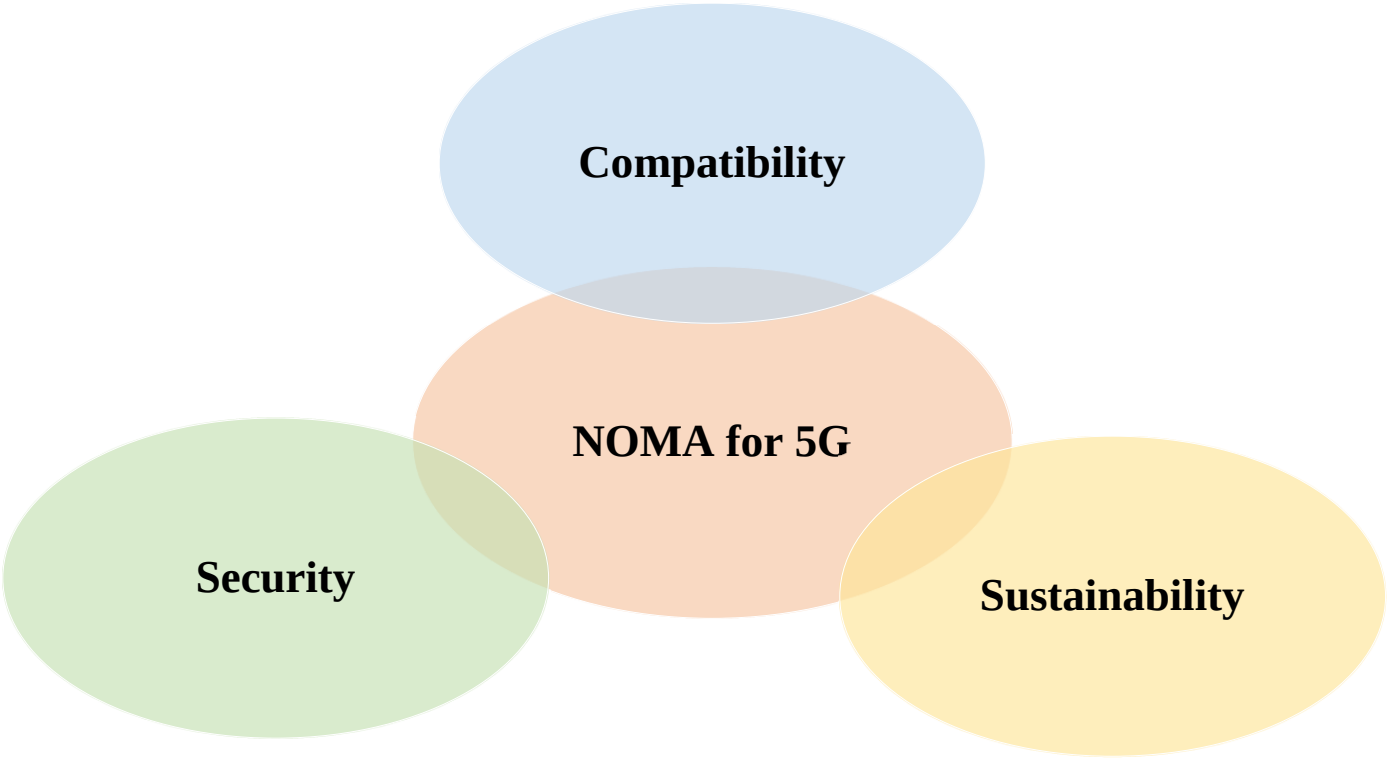
What will NOMA for 6G be?

Intelligent (AI) + Massive (Grant-Free) + Nonorthogonal (Power/Code Domain)+ Compatibility (New techniques)

My Previous Research Contributions in NOMA



http://www.eecs.qmul.ac.uk/∼yuanwei/Publications.html

Signal Processing Advances for NOMA: A Machine Learning Approach

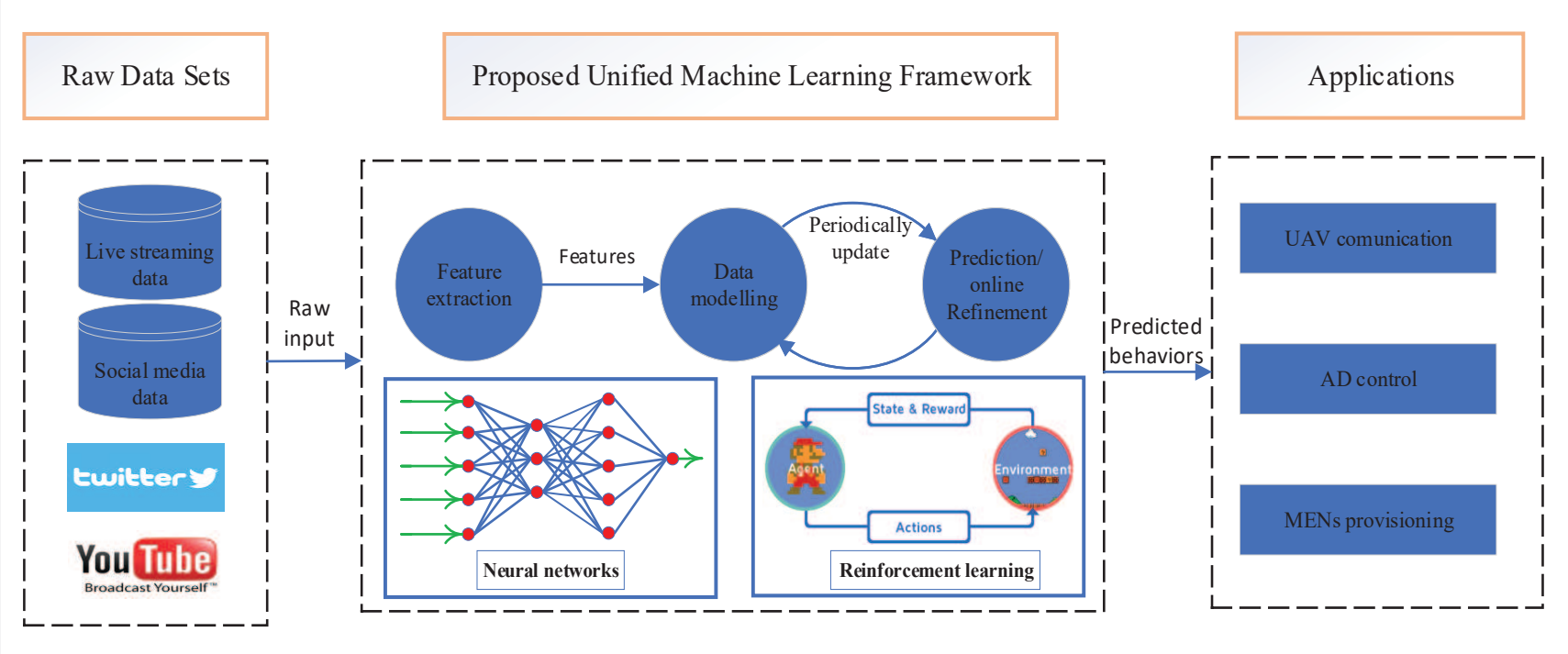


Fig.: Artificial intelligent algorithms for wireless communications.

[1] **Y. Liu**, S. Bi, Z. Shi, and L. Hanzo, "When Machine Learning Meets Big Data: A Wireless Communication Perspective", ***IEEE Vehicular Communication Magazine, vol. 15, no. 1, pp. 63-72, March 2020***, *https://arxiv.org/abs/1901.08329*.

Discussions for Applying Machine Learning in Wireless Communications

- **Two most successful applications for ML**
  - Computer Vision and Natural Language Processing
- **Why and what are the key differences?**
  - Dataset: CV and NLP are data oriented/driven and exist rich dataset
  - Well established mathematical models in wireless communications
- **Before Problem formulation**
  - Can this problem be solved by conventional optimization approach?
  - If yes, what is the key advantages of using machine learning?

Motivation and challenge of AI for NOMA networks

Motivation

- Conventional optimization based methods break down the problem into isolated resource allocation decisions at each time step without considering the long-term effect
- Reinforcement learning (RL) addresses sequential decision making via maximizing a numeric reward signal while interacting with the unknown environment
- **Offline Resource Allocation** RL provides a long-term solution for stochastic optimization problem through exploration (of unknown environment) and exploitation (of known environment).

Challenges

- The hidden relationship between history and future information has no concrete **mathematical expressions**.
- Resource allocation for massive user and base station (BS) connection has high computational complexity.

Case Study: Cache-Aided NOMA MEC

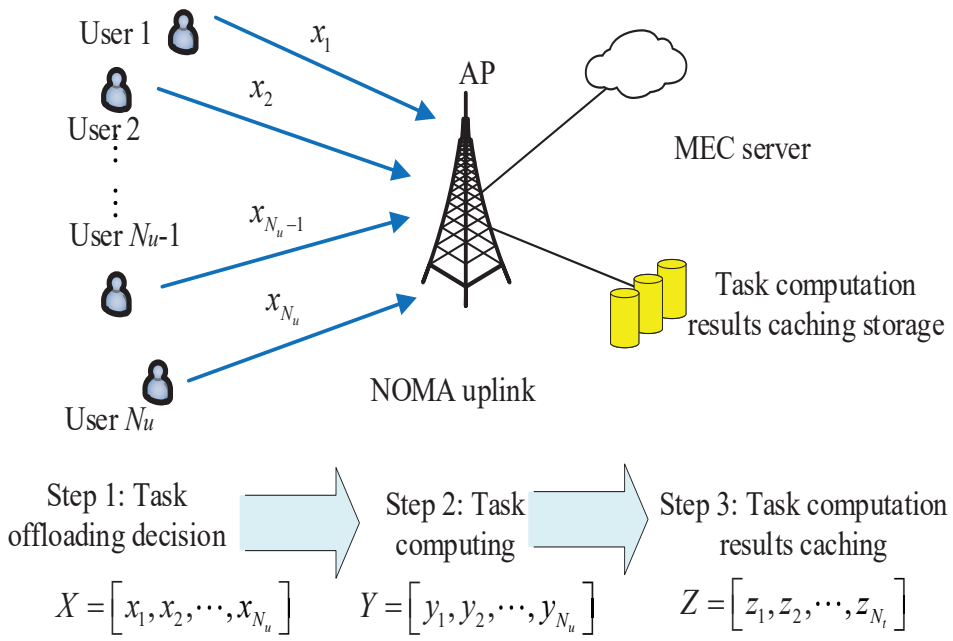


Fig.: An illustration of a multi-user cache-aided MEC.

- Multiple users are served by one MEC server.
- The computation tasks are capable of being computed locally at the mobile devices or in the MEC server.
- The computation results are selectively cached in the storage of the MEC server.

[1] Z. Yang, **Y. Liu**, Y. Chen, N. Al-Dhahir, "Cache-Aided NOMA Mobile Edge Computing: A Reinforcement Learning Approach", ***IEEE Transactions on Wireless Communications***, *https://arxiv.org/abs/1906.08812*.

System Model: Communication Model

The user with higher channel gain is decoded first, the signal-to-interference-plus-noise ratio (SINR) for user i at time t can be given by

$$\mathbf{R_i}(\mathbf{t}) = B\log_2\left(1 + \frac{\rho_i(t)\left|h_i(t)\right|^2}{\sum\limits_{l=i+1}^{N_{up}} \rho_l(t)\left|h_l(t)\right|^2 + \sigma^2}\right), \tag{1}$$

Accordingly, the offloading time for task j with input size π_j at time t is

$$\mathbf{T_{i,j}^{offload}}(\mathbf{t}) = \frac{\pi_j}{\mathbf{R_i}(\mathbf{t})}. \tag{2}$$

Meanwhile, the transmit energy consumption of offloading at time t is given by

$$\mathbf{E_{i,j}^{offload}}(\mathbf{t}) = \rho_i \frac{\pi_j}{\mathbf{R_i}(\mathbf{t})}. \tag{3}$$

System Model: Computation Model

- **Local Computing:** The computing time $\mathbf{T_{i,j}^{loc}}$ and energy consumption $\mathbf{E_{i,j}^{loc}}$ for task j with computational requirement ω_j are

$$\mathbf{T_{i,j}^{loc}} = \frac{\omega_j}{\omega_i^{loc}}. \tag{4}$$

$$\mathbf{E_{i,j}^{loc}} = P_i^{loc} \frac{\omega_j}{\omega_i^{loc}}. \tag{5}$$

- ω_i^{loc}: the local computing capability,
- P_i^{loc}: the energy consumption per second.

- **MEC Computing:** The computing time $\mathbf{T_{i,j}^{mec}}(\mathbf{t})$ and energy consumption $\mathbf{E_{i,j}^{mec}}(\mathbf{t})$ are

$$\mathbf{T_{i,j}^{mec}}(\mathbf{t}) = \frac{\omega_j}{y_i(t)\, C_{MEC}}. \tag{6}$$

$$\mathbf{E_{i,j}^{mec}}(\mathbf{t}) = P^{mec} \frac{\omega_j}{y_i(t)\, C_{MEC}}. \tag{7}$$

- y_i: the proportion of the computing resources allocated from the MEC server,
- P^{mec}: the energy consumption per second at MEC server.

Problem Formulation

The sum energy consumption is

$$\mathbf{E}\left(t, x_i\left(t\right), y_i\left(t\right), z_j\left(t\right)\right) = \left(\mathrm{Pr}_i^j\left(1 - z_j(t)\right)\left(x_i(t)\mathbf{E}_{\mathbf{i,j}}^{\mathbf{loc}} + \left(1 - x_i(t)\right)\mathbf{E}_{\mathbf{i,j}}^{\mathbf{offload}}\left(\mathbf{t}\right) + \left(1 - y_i(t)\right)\mathbf{E}_{\mathbf{i,j}}^{\mathbf{mec}}\left(\mathbf{t}\right)\right)\right). \tag{8}$$

The optimization problem is

$$(\mathbf{P1}) \min_{X,Y,Z} \sum_{t=1}^{T}\sum_{i=1}^{N_u} \mathbf{E}\left(t, x_i\left(t\right), y_i\left(t\right), z_j\left(t\right)\right), \tag{9a}$$

$$\text{s.t.} \quad C_1: \; x_i\left(t\right) \in \{0,1\}, \forall i \in [1, N_u], t \in [1, T], \tag{9b}$$

$$C_2: \; y_i\left(t\right) \in [0,1], \forall i \in [1, N_u], t \in [1, T], \tag{9c}$$

$$C_3: \; z_j\left(t\right) \in \{0,1\}, \forall j \in [1, N_t], t \in [1, T], \tag{9d}$$

$$C_4: \; \sum_{i=1}^{N_u} y_i\left(t\right) = 1, \forall t \in [1, T], \tag{9e}$$

$$C_5: \; \sum_{i=1}^{N_t} z_j\left(t\right) \leq C_{\mathrm{cache}}, \forall t \in [1, T], \tag{9f}$$

Resource allocation: From the Formulated Problem to Reinforcement Learning Model

A Markov decision process (MDP) model is a tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{R} \rangle$.

1. **Objective:** maximize the sum reward $V_\pi(s) = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t r_t \,|s_0 = s \right]$ of a trajectory $s_0 \overset{a_1|r_1}{\rightarrow} s_1 \overset{a_2|r_2}{\rightarrow} s_2 \cdots \overset{a_n|r_n}{\rightarrow} s_n$.
2. **State space ($\mathcal{S}$):** $s(t) = [x(t), y(t), z(t)] \in S = X \times Y \times Z$.
3. **Action space ($\mathcal{A}$):** $a(t) = [\Delta x(t), \Delta y(t), \Delta z(t)] \in A$.
4. **Reward function (r):** the sum energy consumption of taking an action on a state $r_t = \sum_{i=1}^{N_u} \mathbf{E_i}(t-1, s_{t-1}) - \sum_{i=1}^{N_u} \mathbf{E_i}(t, s_t)$.

How to define State and Action Space? From Maze to the Proposed Framework

- **State Space:** High dimensional matrix related to the parameters in the objective function.
- **Action Space:** Moving granularity in each element of the state space.

	Maze game	**UAV trajectory**	**Proposed Problem**
State Space	$s(t)=[x(t),y(t)] \in \mathcal{S}=\mathcal{X}\times\mathcal{Y}$	$s(t)=[x(t),y(t),z(t)] \in \mathcal{S}=\mathcal{X}\times\mathcal{Y}\times\mathcal{Z}$	$s(t)=[x(t),y(t),z(t)] \in \mathcal{S}=\mathcal{X}\times\mathcal{Y}\times\mathcal{Z}$
Action Space	$a(t)=[\Delta x(t),\Delta y(t)]$	$a(t)=[\Delta x(t),\Delta y(t),\Delta z(t)]$	$a(t)=[\Delta x(t),\Delta y(t),\Delta z(t)]$
	2 Dimensional	3 Dimensional	3 Dimensional

Fig.: Setting of state and action space.

Reinforcement Learning Model

The goal of reinforcement learning is to find an optimal policy that maximize the long-term sum rewards:

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t \,|\pi\right]. \quad (10)$$

- Policy π: a function from state to action that specifies what action to take in each state.

The Q-value function is adopted to measure the performance of the policy.

$$Q^*(s,a) = \max_{\pi} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t \,|s = s_0, a = a_0, \pi\right]. \quad (11)$$

The optimal Q-value function satisfies the Bellman Equation

$$Q^*(s,a) = \mathbb{E}_{s' \sim \varepsilon}\left[r + \gamma \max_{a'} Q^*(s', a') \,|s, a\right]. \quad (12)$$

How does the Intelligent Agent Learn?

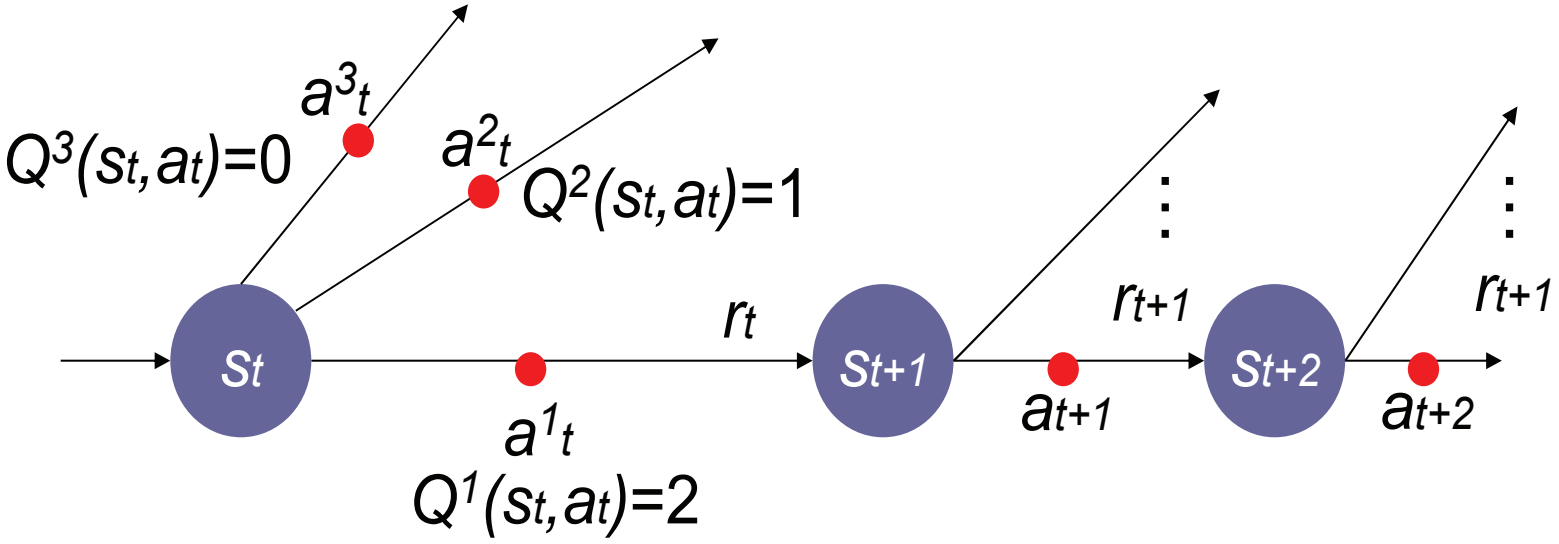
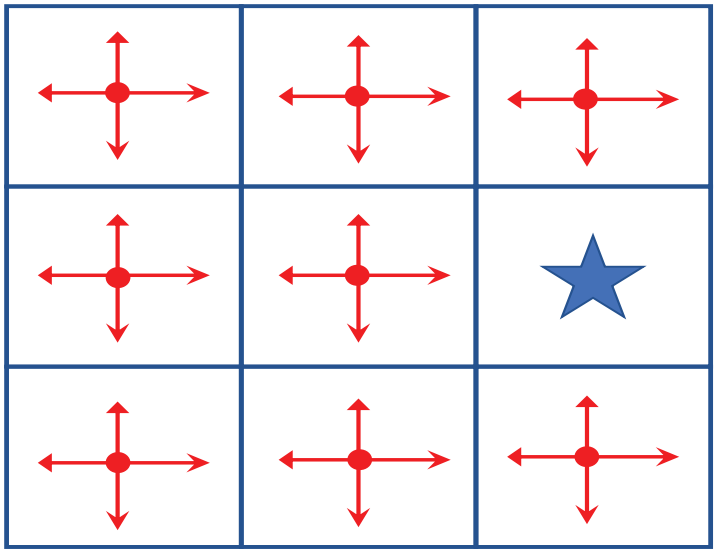


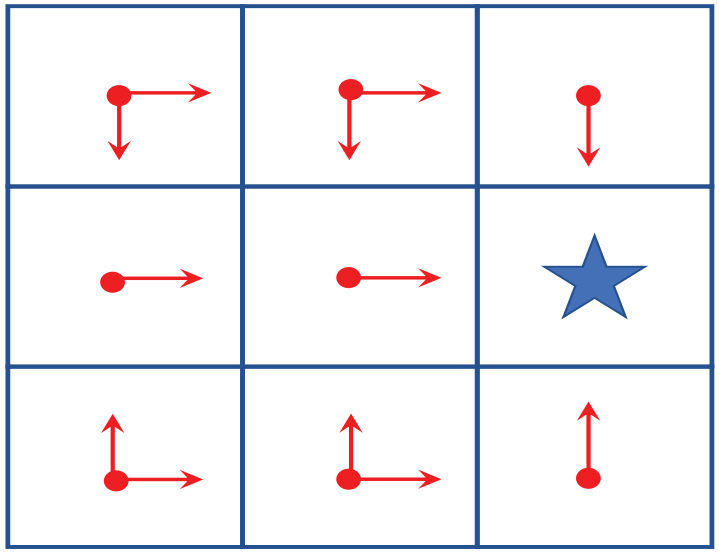
Fig.: Q-learning flow.

- The agent takes action a_t^1, because the corresponding Q value $Q^1(s_t, a_t)$ is max.

The Learning Results: A Maze Case Example



Random policy before learning



Optimal policy after training

Fig.: Q-learning expected result (star represents the treasure).

- After learning, we obtain the optimal action for each state.

Resource Allocation: The Proposed Reinforcement Learning for Cache-Aided NOMA MEC

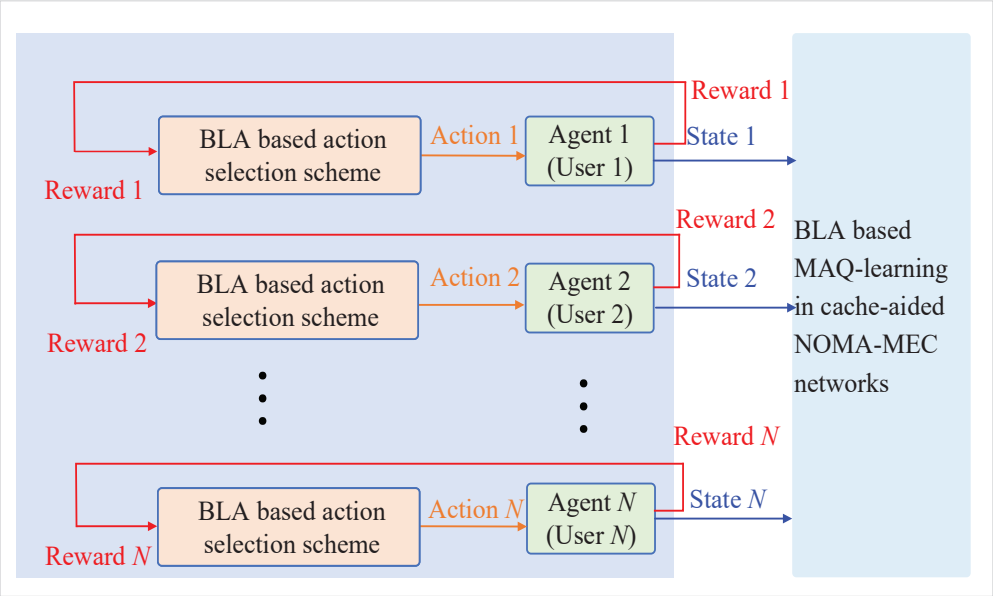


Fig.: Bayesian learning automata based multi-agent Q-learning for resource allocation.

- Each mobile user is set as a intelligent agent.
- Bayesian Learning automata (BLA) is capable of obtaining optimal action for two action case.
- The multiple intelligent agents operate in a selfish manner.

Numerical Results: Resource Allocation (the proposed Reinforcement Learning Algorithm

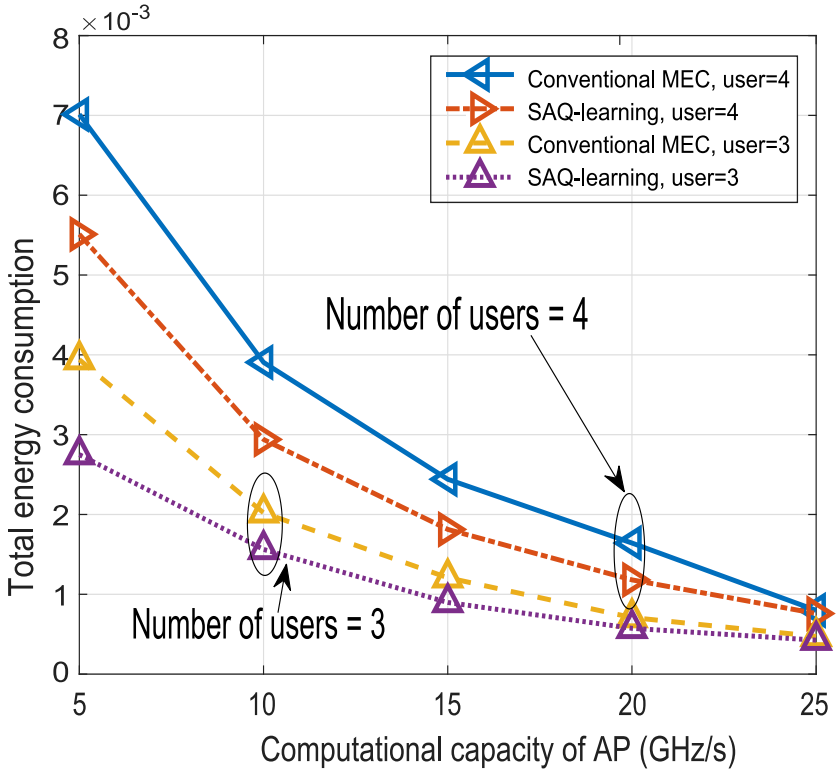


Fig.: Total energy consumption vs. the computation capacity of the AP.

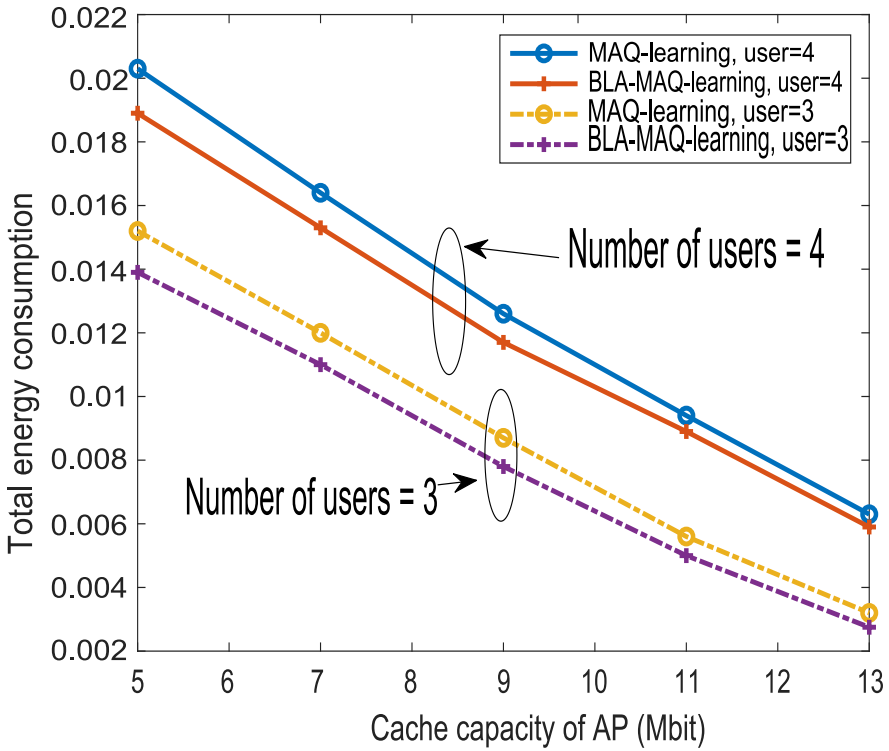


Fig.: Total transmit energy consumption vs. cache capacity of the AP.

Reconfigurable Intelligent Surfaces (RISs) Networks

- **Advantages of RIS [1]**
  - **Easy to deploy**: RISs can be deployed on several structures, including but not limited to building facades, indoor walls [9], aerial platforms, roadside billboards, highway polls.
  - **Spectrum efficiency enhancement**: Meet the diversified demands of services and applications of smart communications, e.g., receivers on the died-zones or in the sky by controllable reflections
  - **Environment friendly**: compared to Relay, more energy efficient.
  - **Compatibility**: RIS can be compatible with the standards and hardware of existing wireless networks
  - This is **Next Generation Relay Networks or MIMO 2.0**.
- **Challenges**
  - **How multiple RISs** reflect received signals?
  - What physical models shall we use?

[1] **Y. Liu**, et. al. "Reconfigurable Intelligent Surfaces: Principles and Opportunities", ***IEEE Communications Survey and Tutorial***, *under review, https://arxiv.org/abs/2007.03435*.

Interplay Between RIS/IRS and NOMA Networks

Motivations

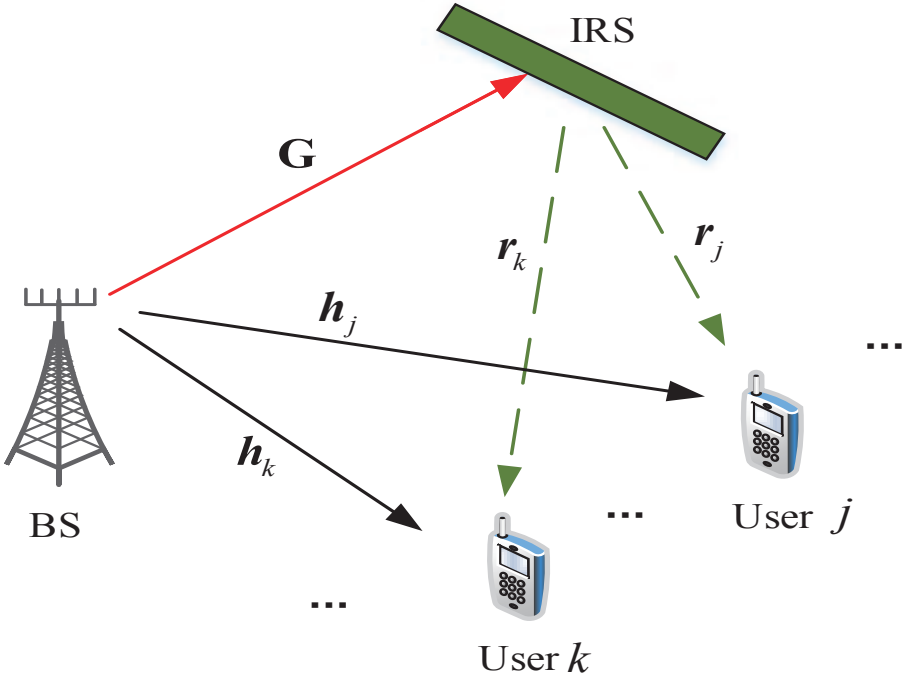
- One the one hand, intelligent reflecting surface **(IRS) to NOMA**: 1) enhance the performance of existing NOMA networks; 2) Provide **high flexibility** for NOMA networks, from channel quality based NOMA to QoS based NOMA; 3) **reduce the constraints** for MIMO-NOMA design as IRS provides additional signal processing ability [1].
- One the other hand, **NOMA to IRS**: NOMA can provide more efficient multiple access scheme for multi-user IRS aided networks.

Challenges

- For multi-antenna NOMA transmission, additional decoding rate conditions need to be satisfied to guarantee successful SIC.
- Both the active and passive beamforming in IRS-NOMA affect the decoding order among users.

[1] T, Hou, **Y. Liu**, Z. Song, X. Sun, and Y. Chen "MIMO-NOMA Networks Relying on Reconfigurable Intelligent Surface: A Signal Cancellation Based Design", ***IEEE Transactions on Communications***, *https://arxiv.org/abs/2003.02117*.

System Model



- An N-antenna base station serves K single-antenna users through the NOMA protocol with the aid of an IRS with M passive reflecting elements
- $\Theta = \mathrm{diag}\,(\mathbf{u}) \in \mathbb{C}^{M\times M}$ denotes the diagonal reflection coefficients matrix of the IRS with $\mathbf{u} = [u_1, u_2, \cdots, u_M]$ and $u_m = \beta_m e^{j\theta_m}$.

[1] X. Mu, **Y. Liu**, L. Guo, J. Lin, N. Al-Dhahir "Exploiting Intelligent Reflecting Surfaces in NOMA Networks: Joint Beamforming Optimization", ***IEEE Transactions on Wireless Communications***, *https://arxiv.org/abs/1910.13636*.

IRS elements assumptions

- **Ideal IRS**: Both the reflection amplitudes and phase shifts can be optimized.

$$\Phi_1 = \left\{ u_m \middle| |u_m|^2 \in [0,1] \right\}. \tag{13}$$

- **Non-ideal IRS**:
  - Continuous phase shifters with the unit modulus constraint.

$$\Phi_2 = \left\{ u_m \middle| |u_m|^2 = 1, \theta_m \in [0, 2\pi) \right\}. \tag{14}$$

  - Discrete phase shifters with B resolution bits:

$$\Phi_3 = \left\{ u_m \middle| |u_m|^2 = 1, \theta_m \in \mathcal{D} \right\}, \tag{15}$$

where $\mathcal{D} = \left\{ \frac{n2\pi}{2^B}, n = 0, 1, 2, \cdots, 2^B - 1 \right\}$.

Received Signal Model

- The received signal at user k can be expressed as

$$y_k = \left(\mathbf{h}_k^H + \mathbf{r}_k^H \Theta \mathbf{G}\right) \sum_{k=1}^{K} \mathbf{w}_k s_k + n_k, \tag{16}$$

- Based on the NOMA principle, the received **SINR** of user j to decode user k is given by

$$\mathrm{SINR}_{k\to j} = \frac{\left|\left(\mathbf{h}_j^H + \mathbf{r}_j^H \Theta \mathbf{G}\right) \mathbf{w}_k\right|^2}{\sum\limits_{\Omega(i)>\Omega(k)} \left|\left(\mathbf{h}_j^H + \mathbf{r}_j^H \Theta \mathbf{G}\right) \mathbf{w}_i\right|^2 + \sigma^2}. \tag{17}$$

- The corresponding decoding rate is $R_{k\to j} = \log_2\left(1 + \mathrm{SINR}_{k\to j}\right)$.
- **Conditions of successful SIC:** $R_{k\to j} \geq R_{k\to k}$ for $\Omega(j) > \Omega(k)$.

Optimization Problem

The considered sum rate maximization problem:

$$(\mathrm{P1}): \max_{\Omega,\Theta,\{\mathbf{w}_k\}} \sum_{k=1}^{K} R_{k\to k} \tag{18a}$$

$$\text{s.t.} \quad R_{k\to j} \geq R_{k\to k},\ \Omega(j) > \Omega(k), \tag{18b}$$

$$\left|\left(\mathbf{h}_k^H + \mathbf{r}_k^H \Theta \mathbf{G}\right) \mathbf{w}_{\Omega(i)}\right|^2 \leq \left|\left(\mathbf{h}_k^H + \mathbf{r}_k^H \Theta \mathbf{G}\right) \mathbf{w}_{\Omega(j)}\right|^2, \forall k, i, j, \Omega(i) > \Omega(j), \tag{18c}$$

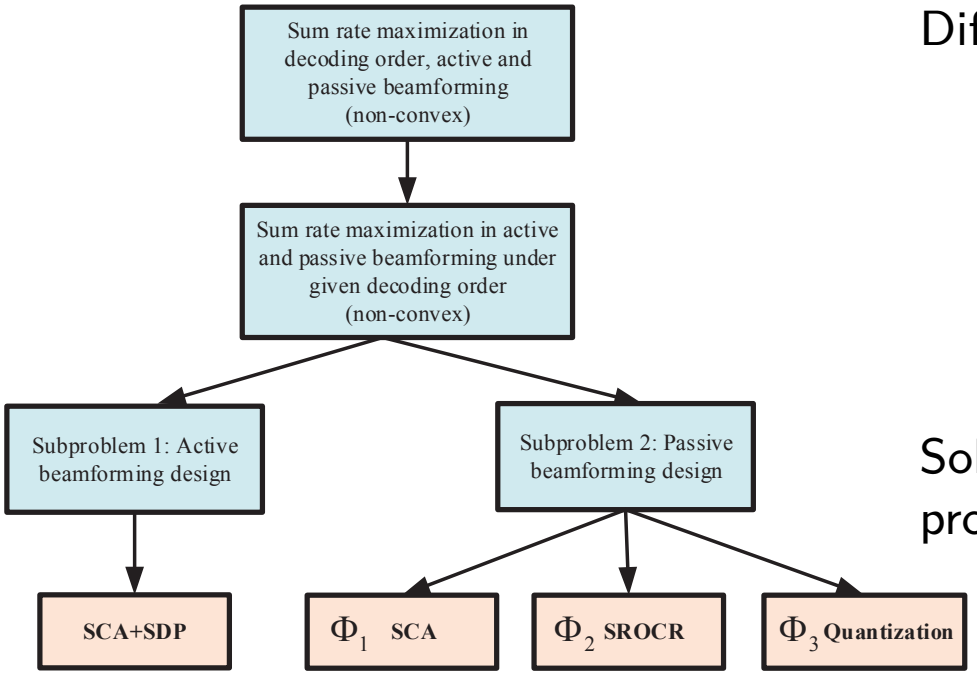
$$\sum_{k=1}^{K} \|\mathbf{w}_k\|^2 \leq P_T \tag{18d}$$

$$u_m \in \Phi, \tag{18e}$$

$$\Omega \in \Pi. \tag{18f}$$

- Φ denotes different IRS assumptions.
- Π denotes the set of all possible SIC decoding orders.

Proposed Solutions



Difficulties:

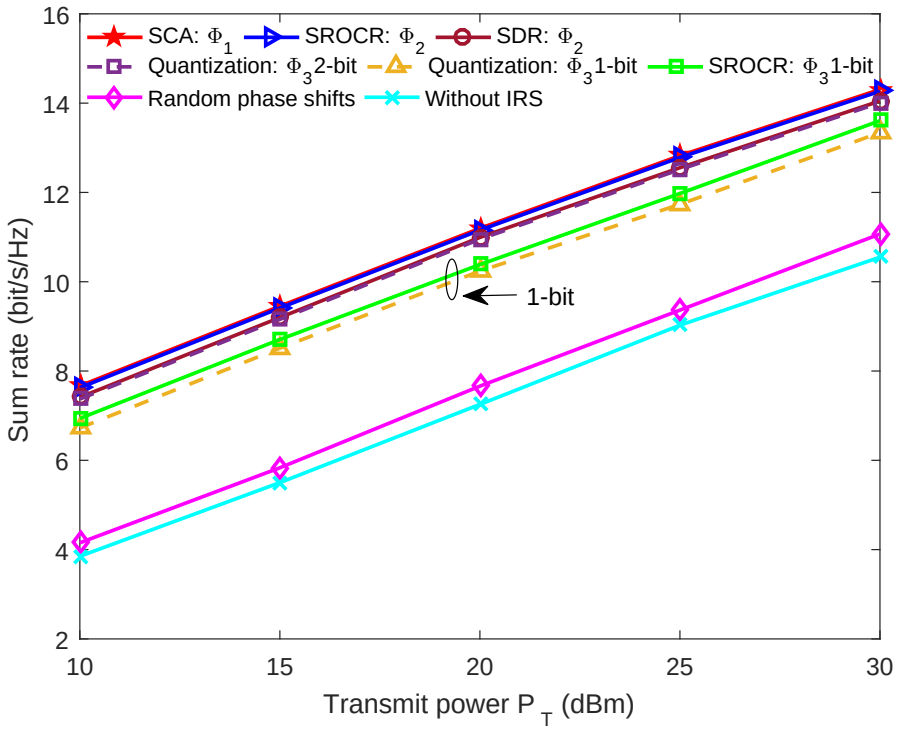
- Decoding order and beamforming vectors are highly coupled.
- Active and passive beamforming vectors both affect the conditions of success SIC.

Solutions:Divide the complicated problem into some ease of subproblems.

[1] X. Mu, **Y. Liu**, L. Guo, J. Lin, N. Al-Dhahir "Exploiting Intelligent Reflecting Surfaces in NOMA Networks: Joint Beamforming Optimization", ***IEEE Transactions on Wireless Communications***, *https://arxiv.org/abs/1910.13636*.

Numerical Results

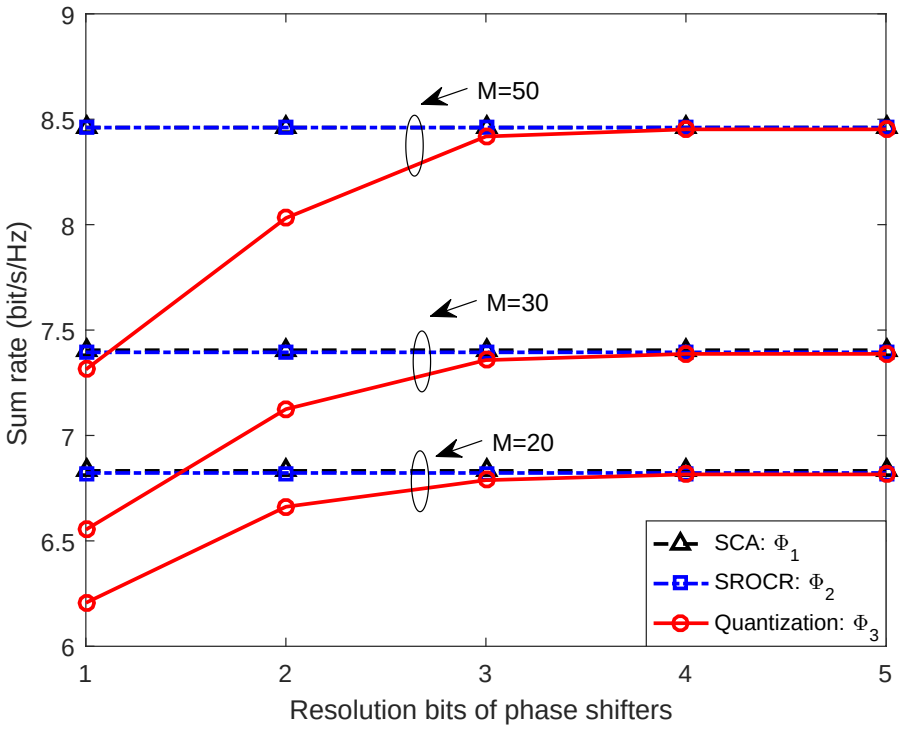
Sum Rate versus Transmit Power



- Significant sum rate gains can be achieved by deploying IRSs with the proposed algorithms.
- The performance gaps between the case of ideal IRS and continuous phase shifters can be ignored.
- The performance degradation caused by finite resolution phase shifters decreases as the bit resolution increases.

Numerical Results

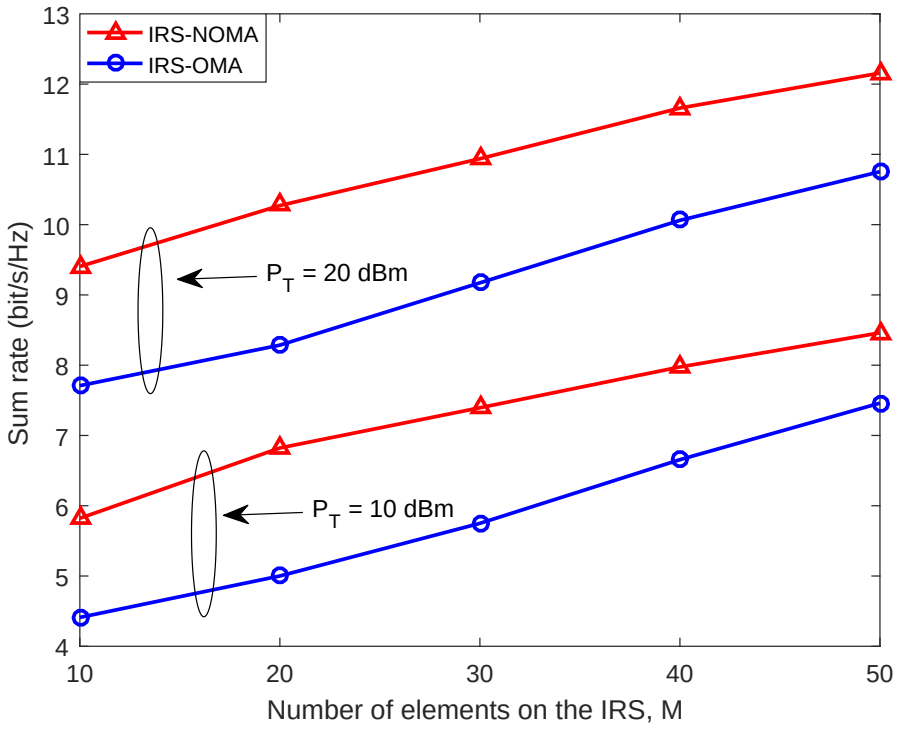
Sum Rate versus the Resolution Bits



- The ideal IRS case achieves the best performance, while the discrete phase shifters case achieves the worst performance.
- "1-bit" and "2-bit" schemes can achieve 80% and 90% performance of the ideal IRS case, respectively.
- The performance loss between the "3-bit" scheme and the ideal IRS is negligible.

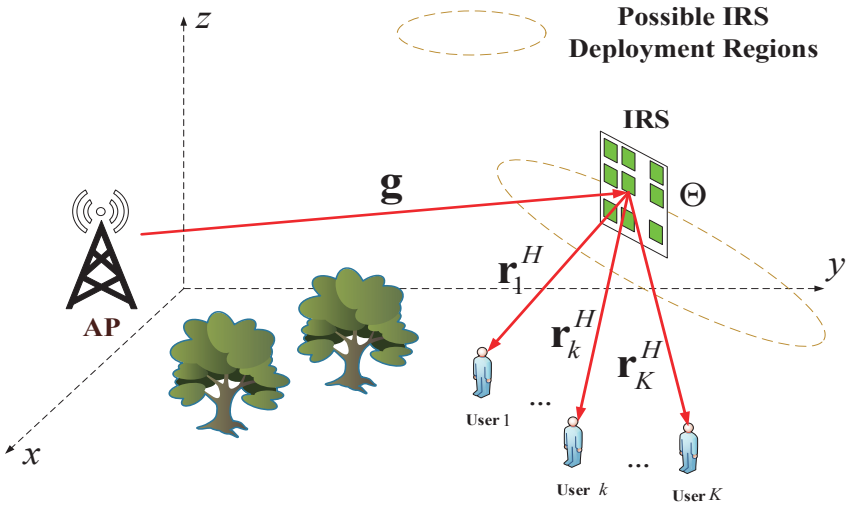
Numerical Results

Performance Comparison with OMA



- The IRS-NOMA scheme significantly outperforms the IRS-OMA scheme since all users can be served simultaneously through the NOMA protocol compared with the OMA scheme.

IRS Deployment and Multiple Access



- An IRS is deployed in a predefined region to assist the downlink transmission from one single-antenna AP to K single-antenna users.
- The locations of the AP, the IRS, and the kth user are denoted by $\mathbf{b} = (x_b, y_b, H_b)^T$, $\mathbf{s} = (x_s, y_s, H_s)^T$, and $\mathbf{u}_k = (x_k, y_k, H_k)^T$, respectively.

[1] X. Mu, **Y. Liu**, L. Guo, J. Lin, R. Schober "Joint Deployment and Multiple Access Design for Intelligent Reflecting Surface Assisted Networks", ***IEEE Transactions on Wireless Communications, under review***, *https://arxiv.org/abs/2005.11544*.

System Model

- For small scale fading, the AP-IRS link and the IRS-user links are modeled as Rician fading channels.
- For large scale fading, the path loss $L_{IRS,k}$ between the AP and user k via the IRS is given by

$$L_{IRS,k} = \frac{\rho_0}{d_{AI}^{\alpha_{AI}}} \frac{\rho_0}{d_{IU,k}^{\alpha_{IU}}}, \tag{19}$$

  which follows the **product-distance path loss model**.
- The combined channel power gain of user k can be expressed as

$$c_k = L_{IRS,k} \left| \mathbf{r}_k^H \Theta \mathbf{g} \right|^2 = \left| \mathbf{q}_k \mathbf{v} \right|^2, \tag{20}$$

  which is determined by **the IRS reflection coefficient** and **deployment location**.

Multiple Access Schemes

- **NOMA**: Let $\mu(k)$ denote the decoding order of user k. The achievable rate of user k in NOMA can be expressed as

$$R_k^N = \log_2\left(1 + \frac{|\mathbf{q}_k\mathbf{v}|^2 p_k}{|\mathbf{q}_k\mathbf{v}|^2 \sum_{\mu(i)>\mu(k)} p_i + \sigma^2}\right), \tag{21}$$

- **FDMA**: AP serves the users in orthogonal frequency bands of equal size.

$$R_k^F = \frac{1}{K}\log_2\left(1 + \frac{|\mathbf{q}_k\mathbf{v}|^2 p_k}{\frac{1}{K}\sigma^2}\right). \tag{22}$$

- **TDMA**: AP serves the users in orthogonal time slots of equal size. The IRS reflection coefficients can assume different values in each time slot, namely, **time-selectivity**.

$$R_k^T = \frac{1}{K}\log_2\left(1 + \frac{|\mathbf{q}_k\mathbf{v}_k|^2 P_{\max}}{\sigma^2}\right), \tag{23}$$

Optimization Problem

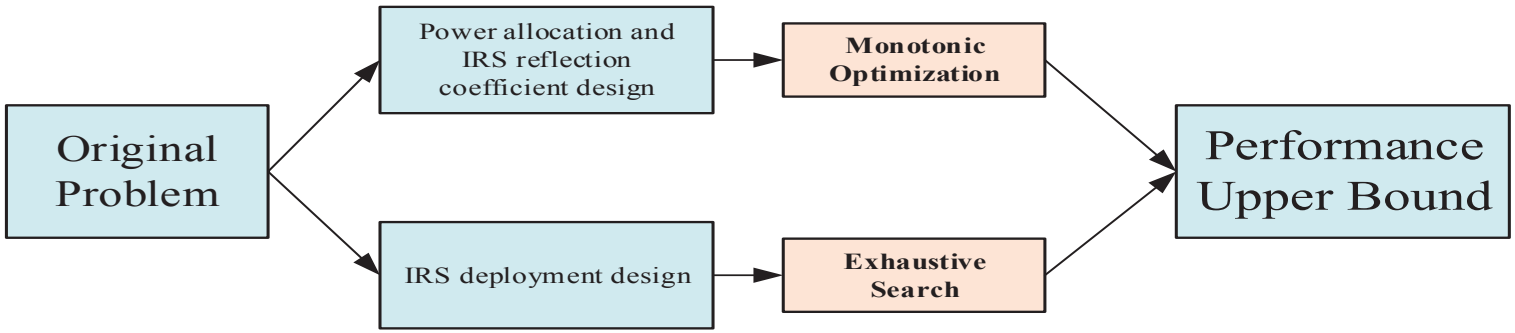
If NOMA is employed, the weighted sum rate (WSR) maximization problem is formulated as follows

$$
\begin{aligned}
(\mathrm{NOMA}): \max_{\{p_k\},\mathbf{v},\mathbf{s}} \quad & \sum_{k=1}^{K} w_k R_k^N && \text{(24a)}\\
\text{s.t.} \quad & \mathbf{s} \in \Omega, && \text{(24b)}\\
& |v_m| = 1, \forall m \in \mathcal{M}, && \text{(24c)}\\
& \mu(k) \in \mathcal{D}, \forall k \in \mathcal{K}, && \text{(24d)}\\
& |\mathbf{q}_k \mathbf{v}|^2 \geq |\mathbf{q}_j \mathbf{v}|^2, \text{if } \mu(k) > \mu(j), && \text{(24e)}\\
& 0 \leq p_k \leq p_j \text{ if } \mu(k) > \mu(j), && \text{(24f)}\\
& \sum\nolimits_{k=1}^{K} p_k \leq P_{\max}, && \text{(24g)}
\end{aligned}
$$

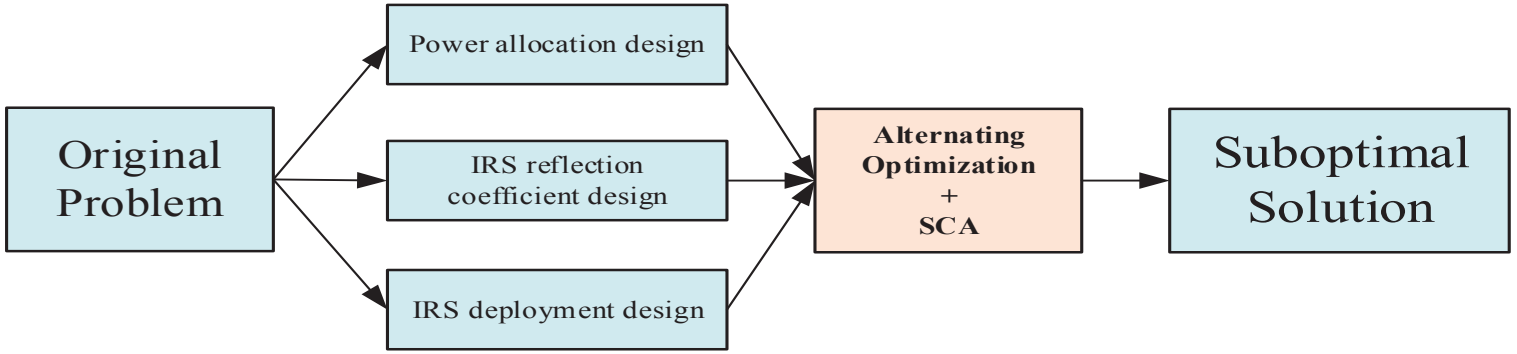
- w_k is the non-negative rate weight for user k.
- Ω denotes possible IRS deployment regions.
- $\mathcal{D}$ denotes all possible decoding order combinations.

Proposed Solutions

- **Monotonic Optimization (MO)-based solution**:



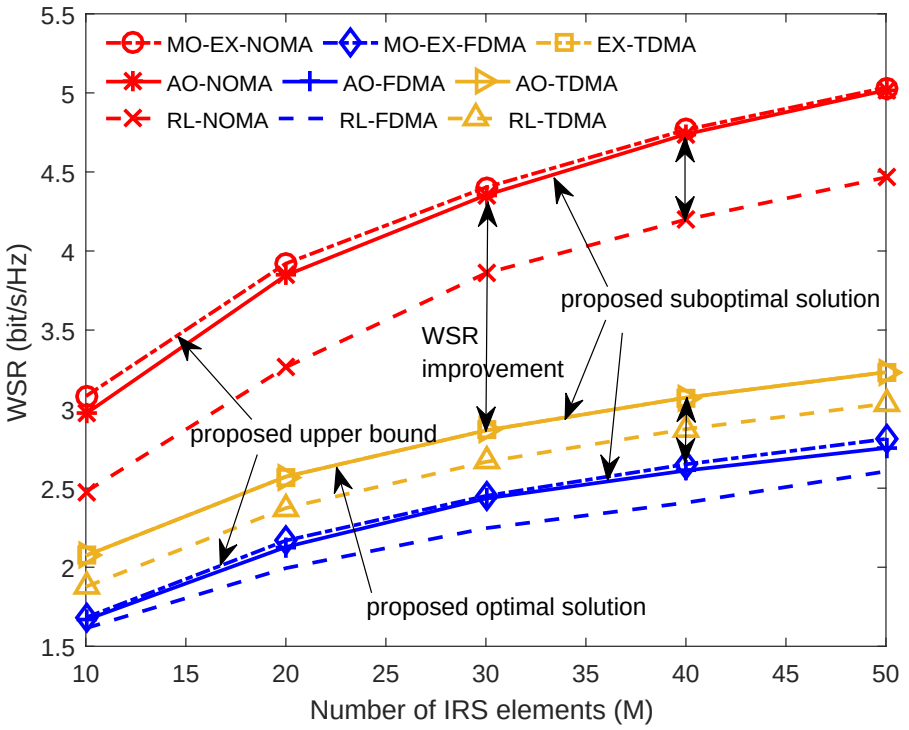
- **Alternating Optimization (AO)-based solution**:



[1] X. Mu, **Y. Liu**, L. Guo, J. Lin, R. Schober "Joint Deployment and Multiple Access Design for Intelligent Reflecting Surface Assisted Networks", ***IEEE Transactions on Wireless Communications, under review***, *https://arxiv.org/abs/2005.11544*.

Numerical Results

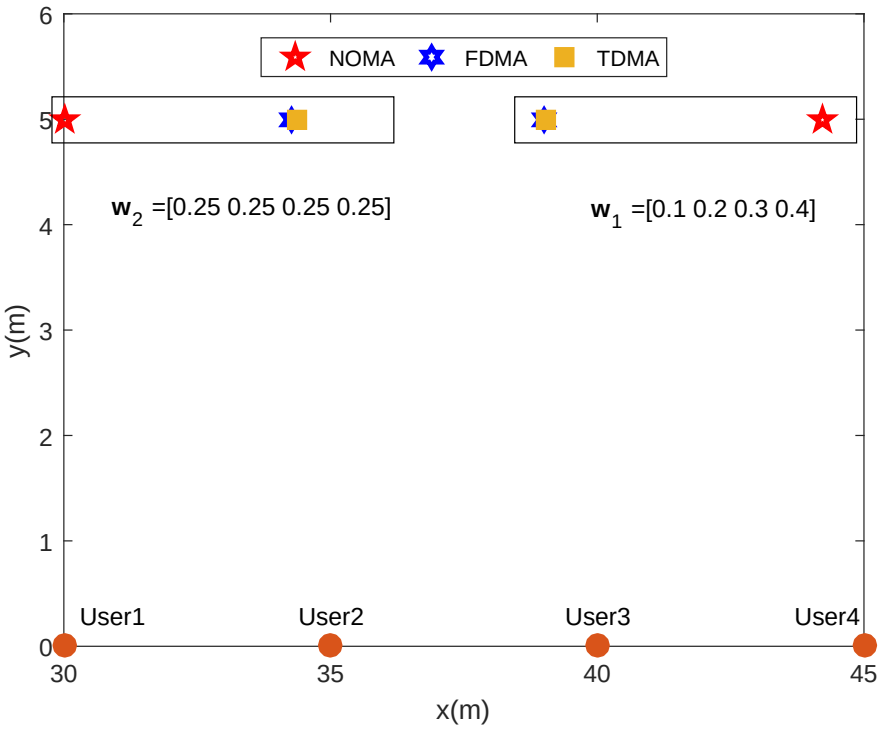
WSR versus the number of IRS elements



- The proposed suboptimal AO algorithms achieve near-optimal performance, closely approaching the proposed upper bound.
- Significant performance gain can be achieved by optimizing the IRS deployment location.
- NOMA has the best performance, and FDMA achieves the worst performance.

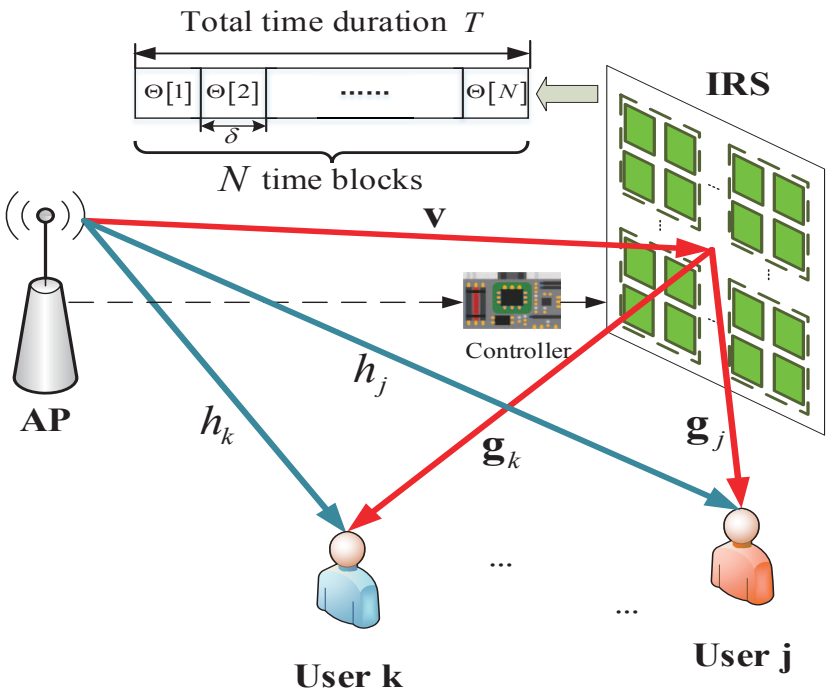
Numerical Results

Optimal IRS Deployment Locations of Different Transmission Schemes



- For NOMA, it is preferable to deploy the IRS in an ***asymmetric*** manner to achieve distinct channel conditions for different users.
- The IRS deployment strategy for OMA is more ***symmetric*** across all users than that for NOMA.

Future Directions: Dynamic IRS Configuration



- The IRS reflection matrix can be reconfigured at the beginning of each time block $n \in \mathcal{N}$ and remains fixed within each time block, i.e. $\Theta[n], n \in \mathcal{N}$.

[1] X. Mu, **Y. Liu**, L. Guo, J. Lin, N. Al-Dhahir "Capacity and Optimal Resource Allocation for IRS-assisted Multi-user Communication Systems", ***IEEE Transactions on Communications, under revision***, *https://arxiv.org/abs/2001.03913*.

Future Directions: Dynamic IRS Configuration

Capacity gain achieved by dynamically reconfiguring the IRS

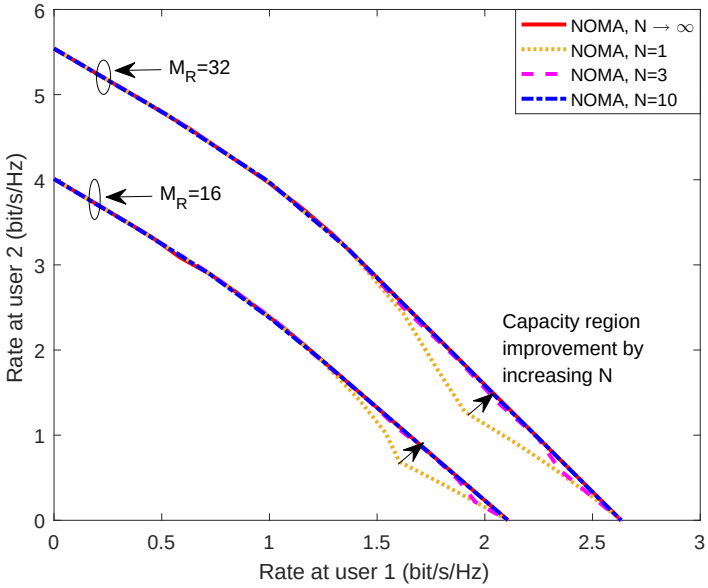


Fig.: Capacity region with NOMA.

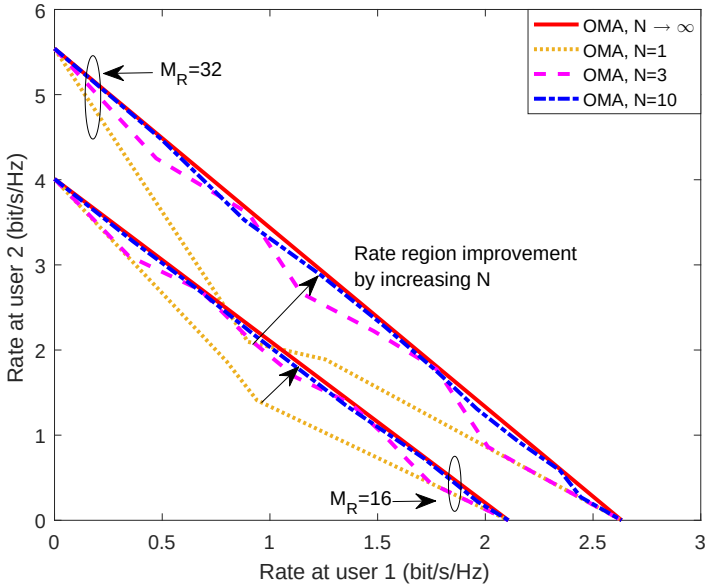


Fig.: Rate region with OMA.

- Dynamically reconfiguring the IRS reflection matrix can increase the capacity gain, especially for OMA;

UAV Communications based on NOMA

Motivations

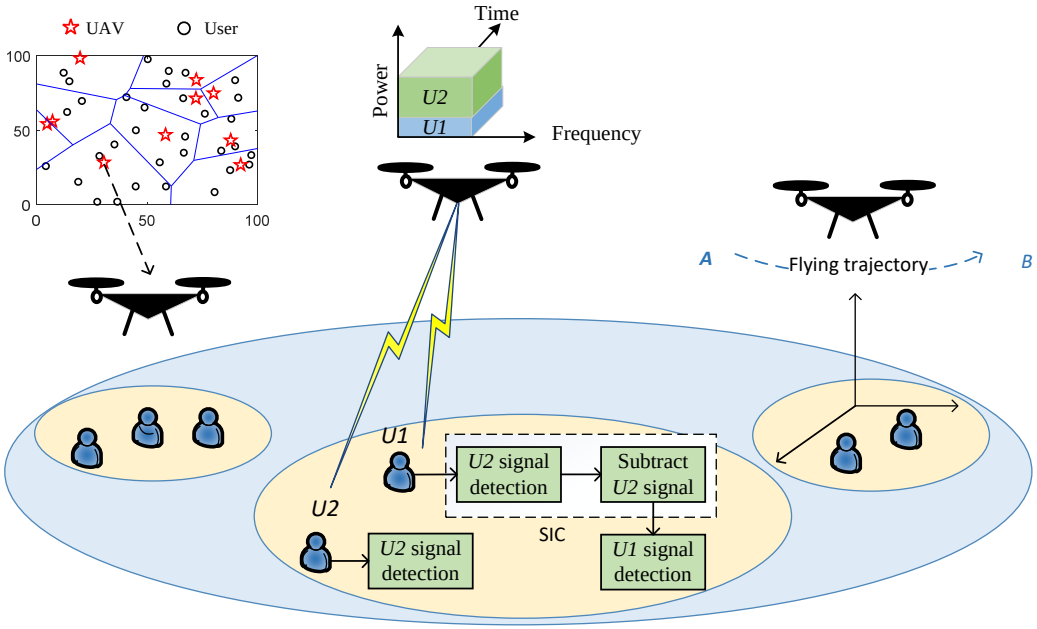
- One the one hand, **NOMA to UAV**: enhance the performance/efficiency/ and improve the connectivity of existing UAV networks.
- One the other hand, **UAV to NOMA**: The distinct channel conditions can be realized (e.g., to pair one static user with one moving UAV user) [1].

Challenges

- New techniques like OTFS may require to exploit the heterogeneous mobility profiles.
- The new mobility models need to be exploited.

[1] X. Mu, **Y. Liu**, L. Guo, and J. Lin, "Non-Orthogonal Multiple Access for Air-to-Ground Communication", ***IEEE Transactions on Communications, accept***, *https://arxiv.org/abs/1906.06523*.

Emerging Applications for NOMA: Exploiting NOMA in UAV Networks



[1] **Y. Liu** *et al.*, "UAV Communications Based on Non-Orthogonal Multiple Access"', ***IEEE Wireless Communications, vol. 26, no. 1, pp. 52-57, Feb. 2019***.

New Technology/Topic to Start/Investigate: NOMA-UAV

My procedure

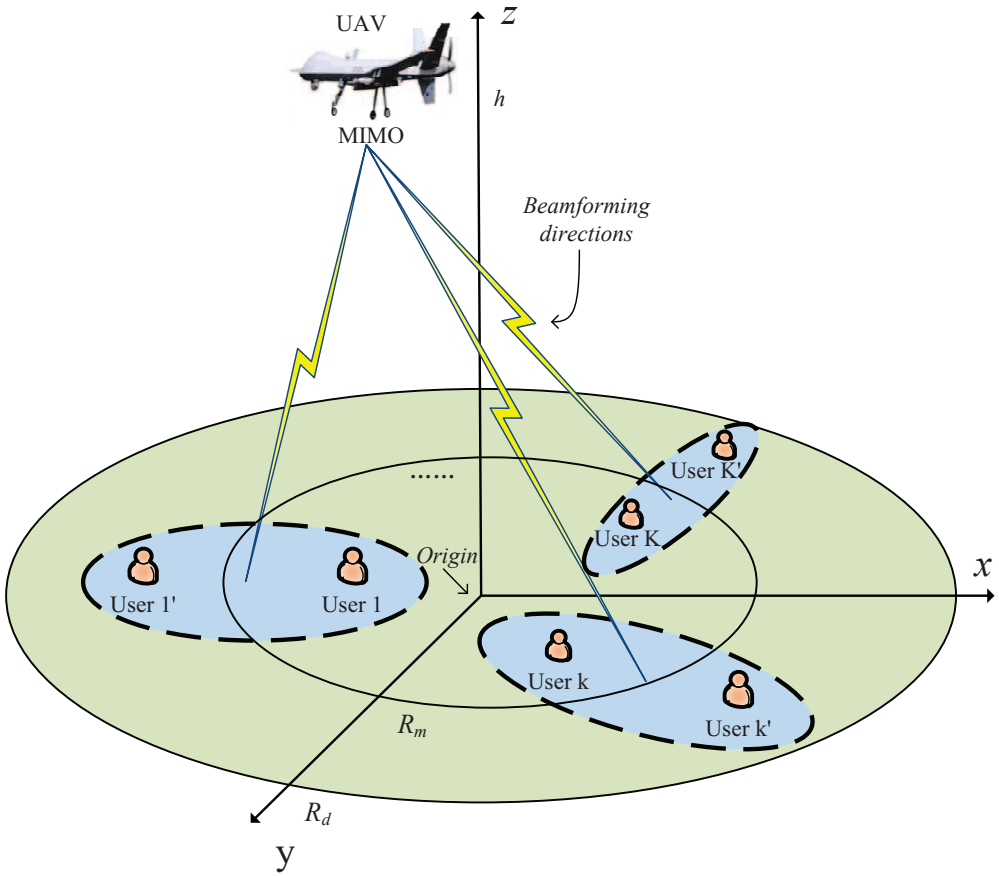
- Step 1: System Modeling, such as channel model (e.g., fading), signal model (e.g., SINR expressions), spatial model.
- Step 2: Find interesting 'spark point' to study: from simple case to complex case with existing mature mathematical tools (e.g., convex optimization, stochastic geometry, matching theory, etc).
- Step 3: Practical scenarios with advanced mathematical tool (e.g., machine learning).

Expected Outcomes

- Step 1: A clean and tidy model to work on.
- Step 2: Good insights compared to existing benchmark schemes.
- Step 3: Exploit the possible timely interesting results.

[1] **Y. Liu** *et al.*, "UAV Communications Based on Non-Orthogonal Multiple Access"', ***IEEE Wireless Communications, vol. 26, no. 1, pp. 52-57, Feb. 2019***.

Single UAV: MIMO-NOMA UAV Networks



- 1) There are probabilistic line-of-sight links.
- 2) The small-scale fading follows Nakagami fading or Rice fading.
- 3) The height of UAV can be a random variable or any arbitrary value.

[1] T. Hou, **Y. Liu**, Z. Song, X. Sun, Y. Chen, "Multiple Antenna Aided NOMA in UAV Networks: A Stochastic Geometry Approach", ***IEEE Transactions on Communications, vol. 67, no. 2, pp. 1031-1044, Feb. 2019***.

From Single UAV to Multiple UAVs: NOMA enabled UAV Communications

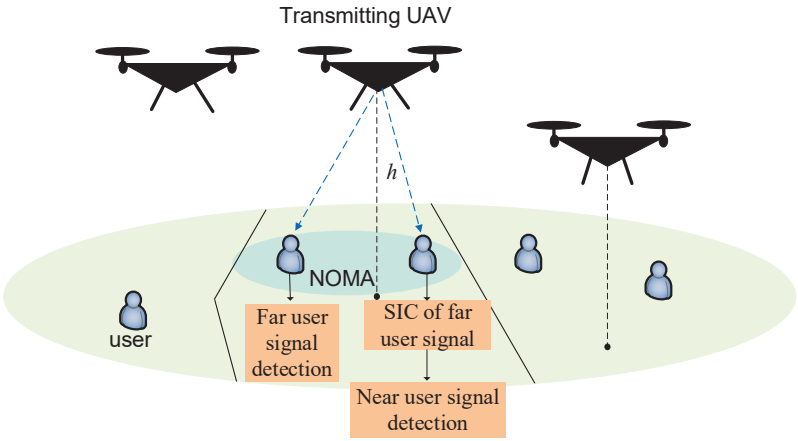


Fig.: An illustration of NOMA UAV in Cellular Networks.

- Massive UAV-BSs are located in the sky.
- Users are located on the ground
- Flexible user-association is required.

[1] T. Hou, **Y. Liu**, Z. Song, X. Sun, Y. Chen, "Exploiting NOMA for Multi-UAV Communications in Large-Scale Networks", ***IEEE Transactions on Communications, accept to appear***.

NOMA enabled UAV Communications—User-centric Scenario

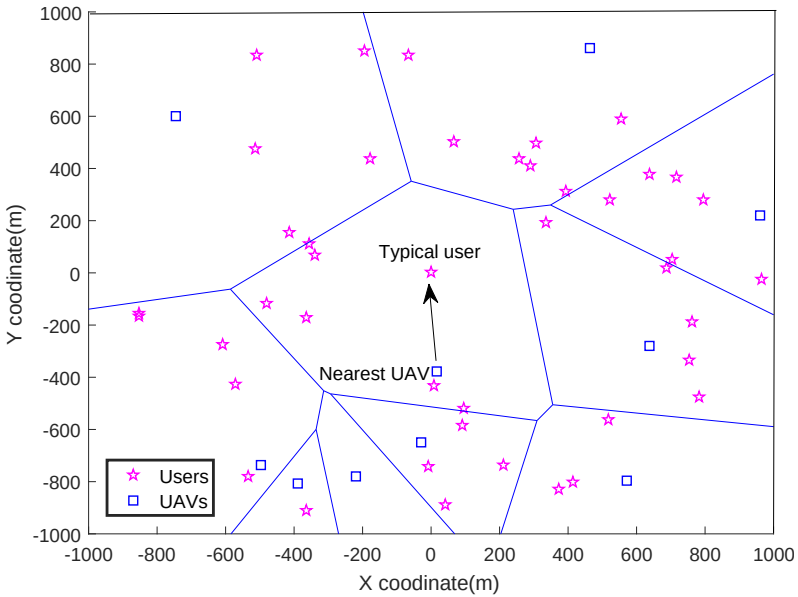


Fig.: The proposed user-centric Scenario, which is a potential solution for emergency communications.

- Ground users and UAVs are distributed according to HPPP.
- All the ground users must be served.
- Association is decided by users according to distance.

NOMA enabled UAV Communications—UAV-centric Scenario

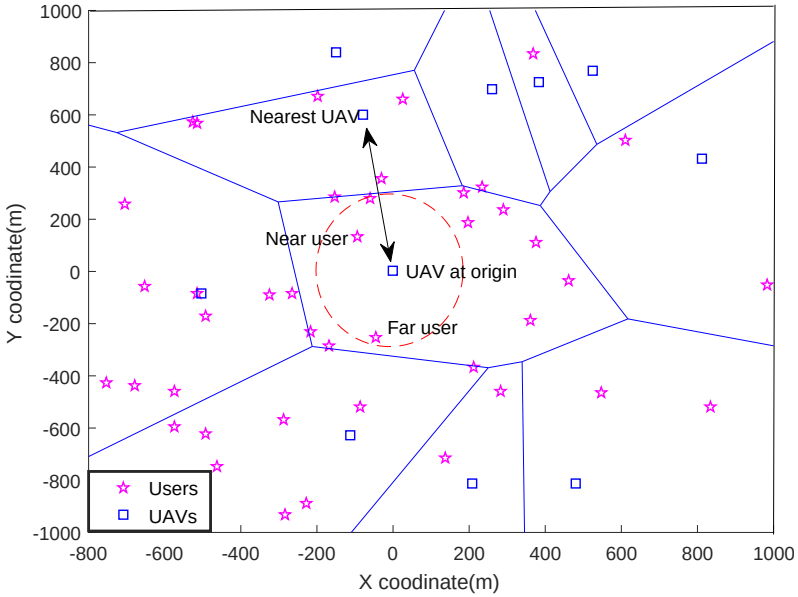


Fig.: The proposed UAV-centric Scenario, which is a potential solution for offloading communications.

- Ground users and UAVs are distributed according to HPPP.
- UAV only provides access services to users located in hot spot areas (e.g., offloading).
- This is supplementary communications.

NOMA UAV-to-Everything (U2X) Networks: From 2D to 3D

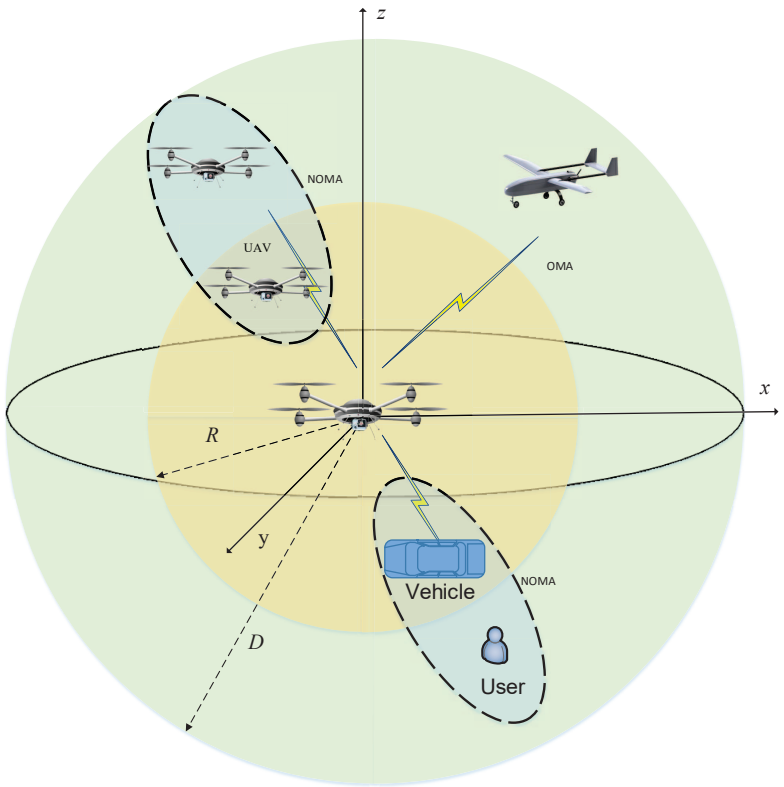
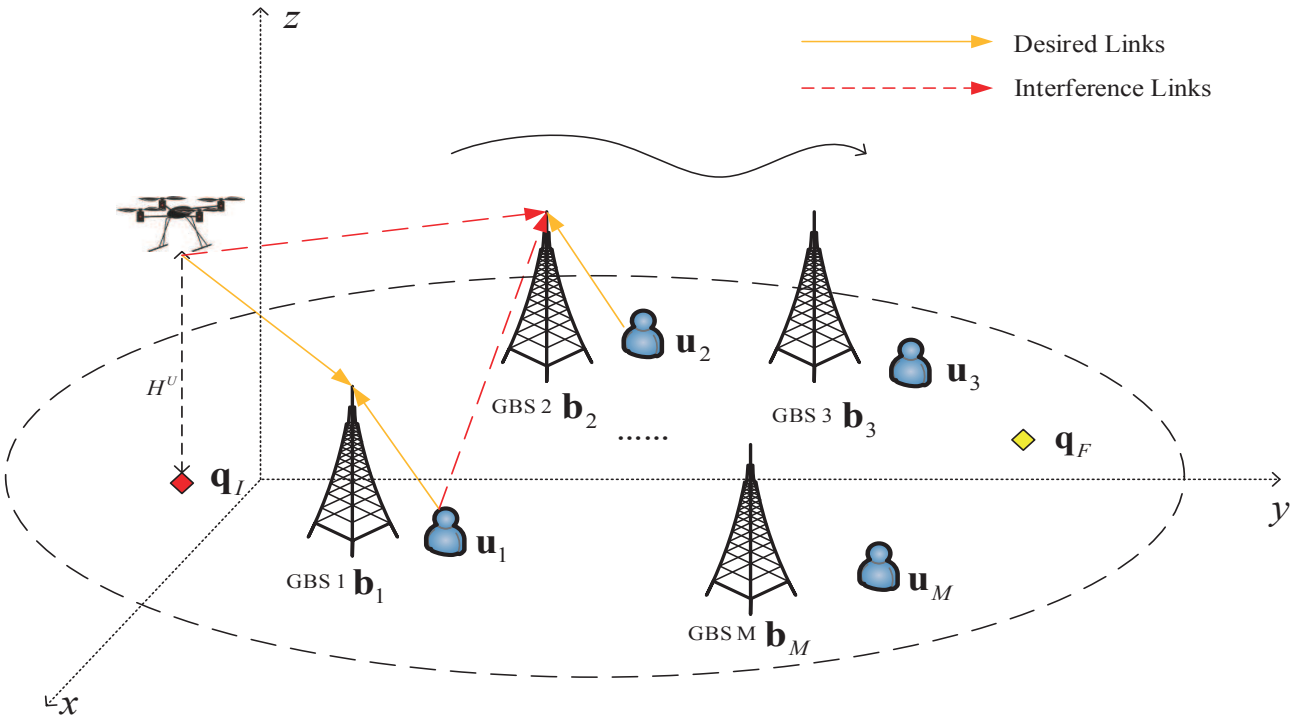


Fig.: The illustration of NOMA enhanced UAV-to-Everything networks.

- Users or receivers are located on the ground or in the sky.
- The coverage space is a sphere.
- NOMA is deployed for providing enhanced connectivity.

[1] T. Hou, **Y. Liu**, Z. Song, X. Sun, Y. Chen, "Non-Orthogonal Multiple Access in UAV-to-Everything (U2X) Networks", ***IEEE Internet of Things, accept to appear***, *https://arxiv.org/abs/1907.05571*.

Air-to-Ground NOMA: Trajectory Design and Resource Allocation



- A rotary-wing UAV has a mission of travelling from an predefined initial location $\mathbf{q}_I$ to a final location $\mathbf{q}_F$, while uploading specific information bits to M GBSs.

[1] X. Mu, **Y. Liu**, L. Guo, and J. Lin, "Non-Orthogonal Multiple Access for Air-to-Ground Communication", ***IEEE Transactions on Communications, accept***, *https://arxiv.org/abs/1906.06523*.

System Model—SINR for the UAV

Based on the aforementioned assumptions, the instantaneous received signal-to-interference-plus-noise ratio (SINR) for the UAV user at mth GBS can be expressed as

$$\gamma_m^{UAV}(t) = \frac{\left|h_m^{UAV}(t)\right|^2 p^{UAV}}{\sum_{j=1}^{M}\left|h_{j,m}^{UE}\right|^2 p_j^{UE} + \sigma^2}, \tag{25}$$

The total uploaded information bits that UAV transmits to GBS m with a bandwidth W during mission completion time T is expressed as

$$\begin{aligned} U_m &= \int_0^T W R_m^{UAV}(t)dt \\ &= \int_0^T a_m(t)\, W \log_2\left(1 + \frac{\left|h_m^{UAV}(t)\right|^2 p^{UAV}}{\sum_{j=1}^{M}\left|h_{j,m}^{UE}\right|^2 p_j^{UE} + \sigma^2}\right) dt. \end{aligned} \tag{26}$$

System Model—SINR for GUEs

Similarly, the instantaneous received SINR for the GUE m at mth GBS can be expressed as

$$\gamma_m^{UE}(t) = \frac{S_m}{(1 - a_m(t)) \left| h_m^{UAV}(t) \right|^2 p^{UAV} + I_m}, \tag{27}$$

where $S_m = \left| h_{m,m}^{UE} \right|^2 p_m^{UE}$ and $I_m = \sum_{j=1, j \neq m}^{M} \left| h_{j,m}^{UE} \right|^2 p_j^{UE} + \sigma^2$. Different from the received SINR of UAV, (27) implies two different scenarios for GUEs.

- First, when UAV is associated with GBS m, $a_m(t) = 1$, the paired GUE's signal is decoded without UAV interference owing to SIC.
- Second, when GUE is served by non-associated GBS, $a_m(t) = 0$, the communication rate of GUE will be degraded due to the UAV interference.

The achievable rate of GUE m at time instant t is

$$R_m^{UE}(t) = \log_2 \left(1 + \gamma_m^{UE}(t)\right). \tag{28}$$

System Model—Uplink NOMA Zone

When UAV is associated with GBS m at time instant t for data transmission, the following constraint should be meet to perform SIC successfully in uplink NOMA communication:

$$\left|h_m^{UAV}(t)\right|^2 p^{UAV} \geq S_m, \tag{29}$$

which can be further expressed as

$$0 \leq \|\mathbf{q}(t) - \mathbf{b}_m\|^2 \leq D_m^{NOMA}, \tag{30}$$

where $D_m^{NOMA} = \frac{\beta_0}{S_m} - H^2$, $\beta_0 = \rho_0 p^{UAV}$ and $H = H^U - H^G$. (30) means if and only if the horizontal distance between UAV and GBS m is no larger than $\sqrt{D_m^{NOMA}}$, the UAV can associate with GBS m through uplink NOMA protocol. We thus define a disk region on the horizontal plane centered at $\mathbf{b}_m$ with radius $\sqrt{D_m^{NOMA}}$ as the ***uplink NOMA zone***.

System Model—QoS Protected Zone

Define θ_m as the QoS requirement of GUE m. During the UAV mission completion time T, the instantaneous achievable rate constraint of GUE m can be expressed as

$$R_m^{UE}(t) \geq \theta_m, 0 \leq t \leq T. \tag{31}$$

$R_m^{UE}(t)$ depends on the UAV-GBS association state, we only need to concentrate on the interfering scenario. Constraint (33g) can be expressed as

$$\|\mathbf{q}(t) - \mathbf{b}_m\|^2 \geq D_m^{QoS}. \tag{32}$$

where $D_m^{QoS} = \frac{\beta_0}{\frac{S_m}{2^{\theta_m}-1} - I_m} - H^2$. Similar with the definition of the uplink NOMA zone, (32) means when the UAV is not associated with GBS m, the horizontal distance between the UAV and GBS m should not be smaller than $\sqrt{D_m^{QoS}}$ in order to guarantee the QoS requirement of GUE m. We define another disk region centered at $\mathbf{b}_m$ with radius $\sqrt{D_m^{QoS}}$ as the ***QoS protected zone*** for GUE m and the UAV cannot stay in when it is not associated with GBS m.

Optimization Problem

The considered UAV mission complete time minimization problem:

$$
\begin{aligned}
(\mathrm{P1}): \min_{\mathbf{Q},\mathbf{A},T} \quad & T && \text{(33a)}\\
\text{s.t.} \quad & \mathbf{q}(0) = \mathbf{q}_I, && \text{(33b)}\\
& \mathbf{q}(T) = \mathbf{q}_F, && \text{(33c)}\\
& \|\dot{\mathbf{q}}(t)\| \leq V_{\max}, 0 \leq t \leq T, && \text{(33d)}\\
& U_m \geq \widetilde{U}_m, m \in \mathcal{M}_{BS}, && \text{(33e)}\\
& a_m(t) \|\mathbf{q}(t) - \mathbf{b}_m\|^2 \leq D_m^{NOMA}, \forall m \in \mathcal{M}_{BS}, 0 \leq t \leq T, && \text{(33f)}\\
& \|\mathbf{q}(t) - \mathbf{b}_m\|^2 \geq (1 - a_m(t)) D_m^{QoS}, \forall m \in \mathcal{M}_{BS}, 0 \leq t \leq T, && \text{(33g)}\\
& \sum_{m=1}^{M} a_m(t) = 1, 0 \leq t \leq T, && \text{(33h)}\\
& a_m(t) \in \{0,1\}, \forall m \in \mathcal{M}_{BS}. && \text{(33i)}
\end{aligned}
$$

Optimization Problem

- Constraints (33b)-(33d) are the UAV mobility constraints.
- Constraint (33e) are the required UAV uploading information bits of each GBSs.
- Constraints (33f) and (33g) represent the UAV is required to stay in the specific feasible regions when it is associated with different GBSs.
- Constraints (33h) means the UAV need to maintain connectivity during T and associate with at most one GBS at each time instant.

There are two main reasons that make Problem (P1) is challenging to solve.

- First, (P1) is a mixed integer non-convex problem due to the non-convex constraints (33e) and integer constraints (33i). Constraints (33f) and (33g) further make $\mathbf{Q}$ and $\mathbf{A}$ coupled together.
- Second, the UAV trajectory $\mathbf{Q}$ and the UAV-GBS association vectors $\mathbf{A}$ are continuous functions of t, which make (P1) involve infinite number of optimization variables.

Proposed Solutions: Fly-Hover-Fly Scheme

Theorem 1: Without lose of optimality to (P1), the optimal UAV trajectory can be assumed to be following fly-hover-fly structure: Except hovering at specific locations, the UAV travels at maximum speed V_{max}.
Based on **Theorem 1**, the total mission completion time of (P1) can be expressed as

$$\begin{aligned} T\left(D_{fly}\right) &= T_{fly} + T_{hover} \\ &= \sum_{m=1}^{M} \left(\frac{D_{fly,m}}{V_{\max}} + \frac{\widetilde{U}_m - U_{fly,m}}{R_{hover,m}} \right) \\ &= \frac{D_{fly}}{V_{\max}} + \sum_{m=1}^{M} \frac{\widetilde{U}_m - U_{fly,m}}{R_{hover,m}}. \end{aligned} \tag{34}$$

where $D_{fly,m}$ is the total travelling distance when UAV is associated with GBS m, $U_{tr,m}$ is the UAV uploaded information bits to GBS m during travelling through $D_{fly,m}$ and $R_{hover,m}$ is the communication rate when UAV is associated with GBS m and hovers at the corresponding optimal location.

Shortest Path Construction: A Graph Theory View

Now, the problem becomes to find the shortest path from $\mathbf{q}_I$ to $\mathbf{q}_F$ while visiting all hovering locations $\{\mathbf{q}_m\}$. To tackle this problem, we construct an undirected weighted graph denoted by $G_1 = (V_1, E_1)$, where the vertices set V_1 is given by

$$V_1 = \{\mathbf{q}_I, \mathbf{q}_1, \mathbf{q}_2, \cdots, \mathbf{q}_M, \mathbf{q}_F\}. \tag{35}$$

The edge set E_1 is given by

$$E_1 = \{(\mathbf{q}_i, \mathbf{q}_j), i \neq j \in \{\mathcal{M}_{BS}\} \cup \{I, F\}\}. \tag{36}$$

The weight of each edge is $d(\mathbf{q}_i, \mathbf{q}_j)$, which represents the shortest path length between two vertices.

Shortest Path Construction: A Modified Travel Salesman Problem

Standard TSP:

- The salesman (UAV) needs to start and end with the same city and visit other cities (vertices) only once.

Though the standard TSP is a NP-hard problem, there are many efficient algorithm to solve the standard TSP with time complexity $\mathcal{O}\left(M^2\right)$.

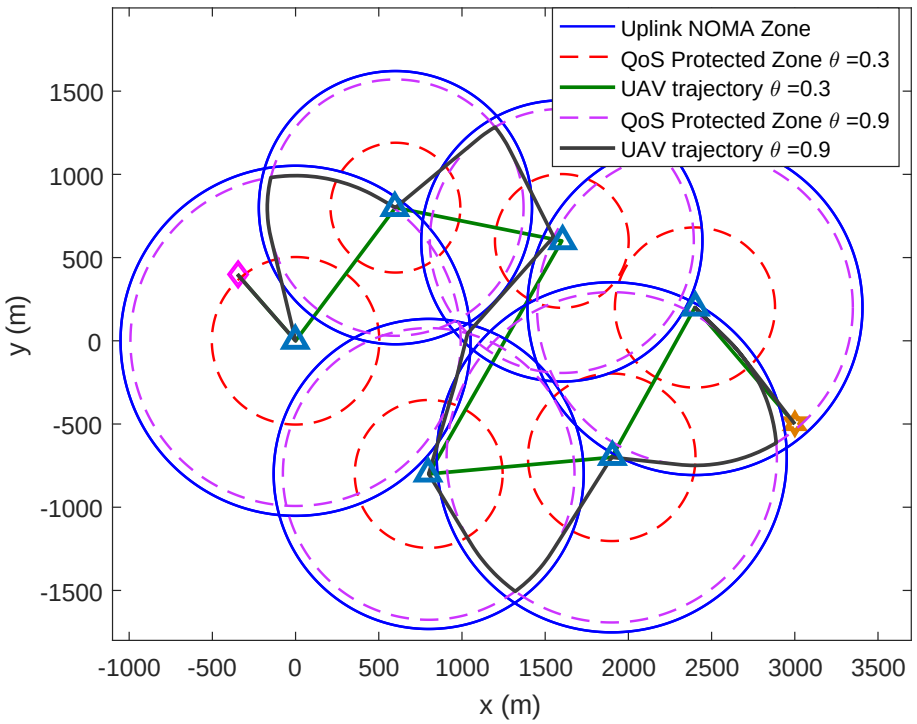
Our Problem – A modified TSP:

- The salesman (UAV) is required to start and end with two different cities (vertices) and visit different cities (vertices) at least once.

Solutions:

- Convert the modified TSP into a standard TSP, which can be efficiently solved.

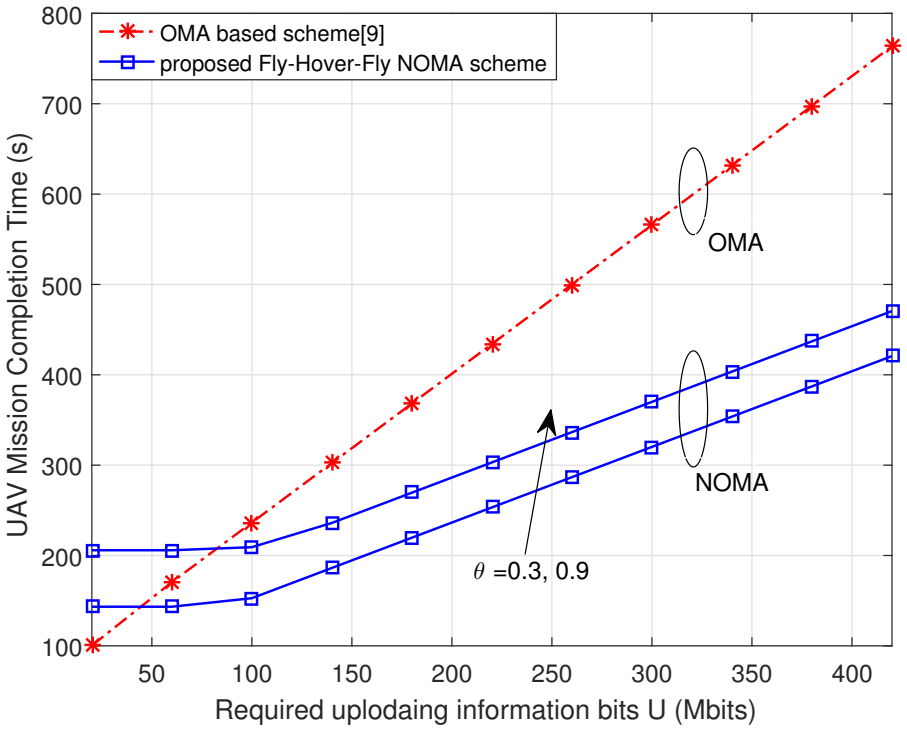
Numerical Results



"△" are the locations of GBSs.
"◊" is the UAV initial location.
"⋆" is the UAV final location.

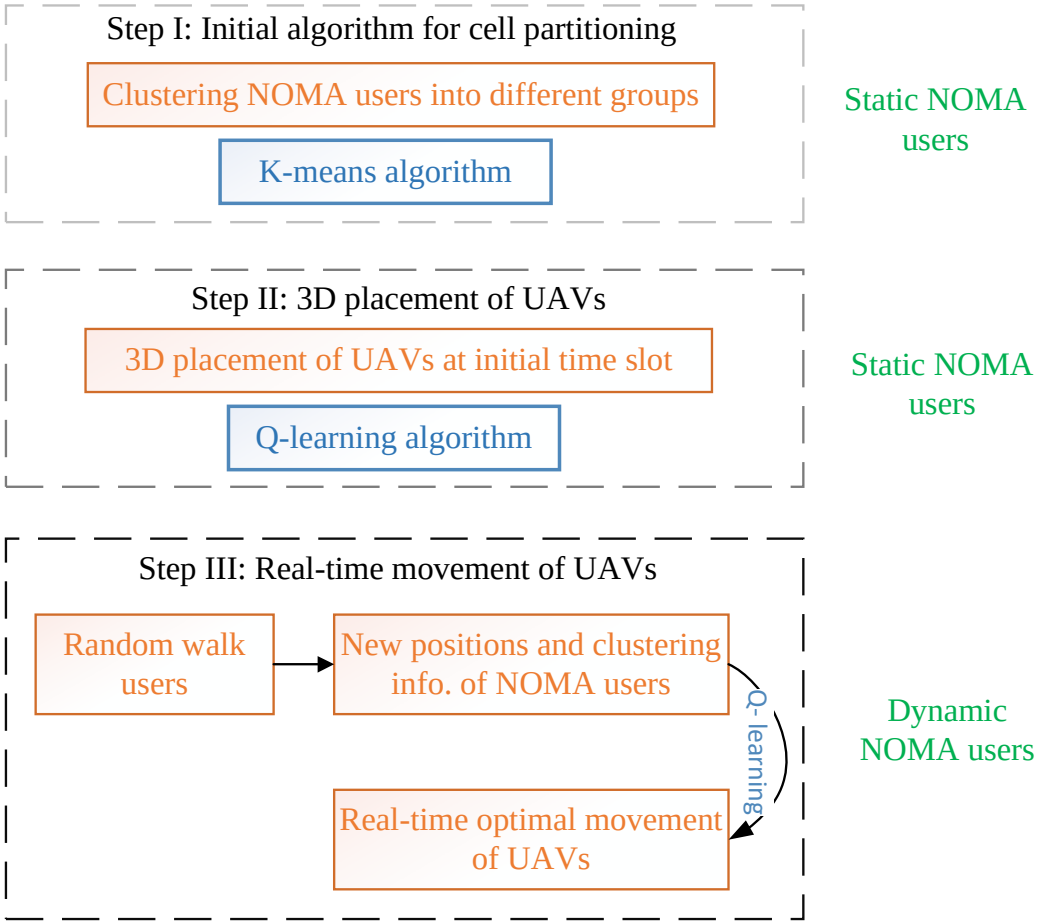
- Higher QoS requirements contribute larger QoS protected zones.
- When $\theta = 0.3$ bit/s/Hz, the designed UAV trajectory (green line) is only composed of several line segments. It is due to the fact that smaller $\left\{D_m^{QoS}\right\}$ impose little constraints on UAV trajectory design..
- When $\theta = 0.9$ bit/s/Hz, the UAV trajectory (black line) is designed to exactly avoid the GUE QoS protected regions to have a shortest travelling distance.

Numerical Results



- The proposed NOMA scheme significantly outperforms OMA scheme when U increase due to the spectrum sharing, which implies the proposed scheme is suitable for rate demanding UAV communication.
- When θ increases, the UAV mission completion time increases for same U. This is due to the increase of θ impose more constraints on the UAV trajectory design and enlarge the minimum UAV travelling distance.

Machine Learning for NOMA-UAV networks



[1] **Y. Liu** *et al.*, "UAV Communications Based on Non-Orthogonal Multiple Access"', ***IEEE Wireless Communications, vol. 26, no. 1, pp. 52-57, Feb. 2019***.

Research Opportunities and challenges for NOMA

1. Joint MIMO-NOMA-RIS design.
2. NOMA in Heterogenous Mobility Networks
3. Massive NOMA in IoT Networks
4. Grant/Semi-Grant Free NOMA
5. Error Propagation in SIC.
6. Imperfect SIC and limited channel feedback.
7. Synchronization/asynchronization design for NOMA.
8. Different variants of NOMA.
9. Novel coding and modulation for NOMA.
10. Hybrid multiple access
11. Security provisioning in NOMA

Thank you!

Thank you!