FRIEDRICH-ALEXANDER
UNIVERSITÄT
ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Optimized Resource Allocation for Future Wireless Communication Systems

Doctoral Defense Presentation

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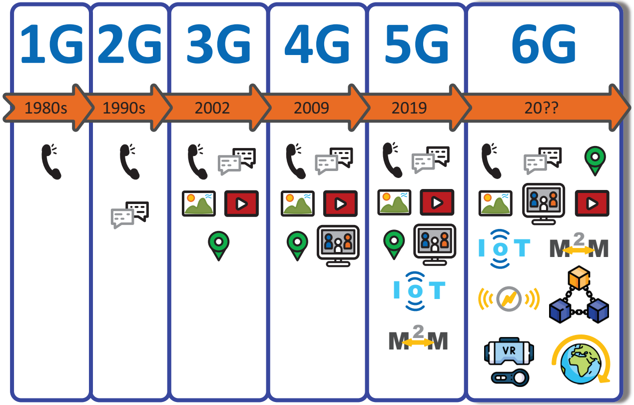
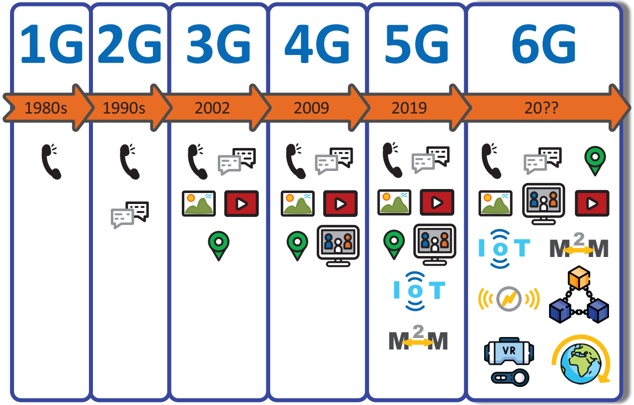
Outline

Background

Evolution of the wireless communication network



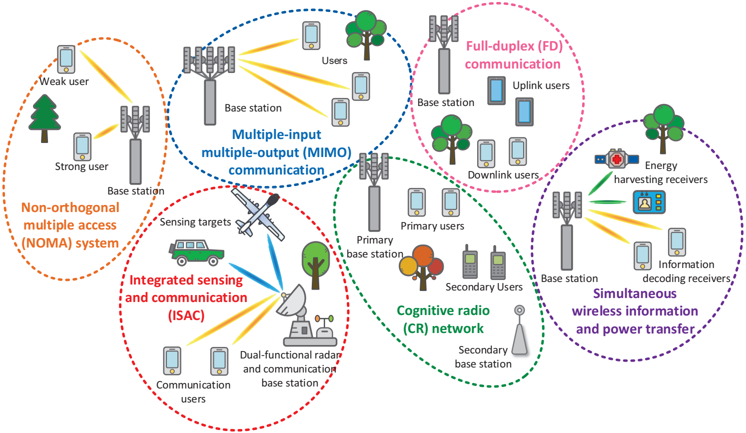
Evolution of the wireless communication network



Requirements for the sixth-generation

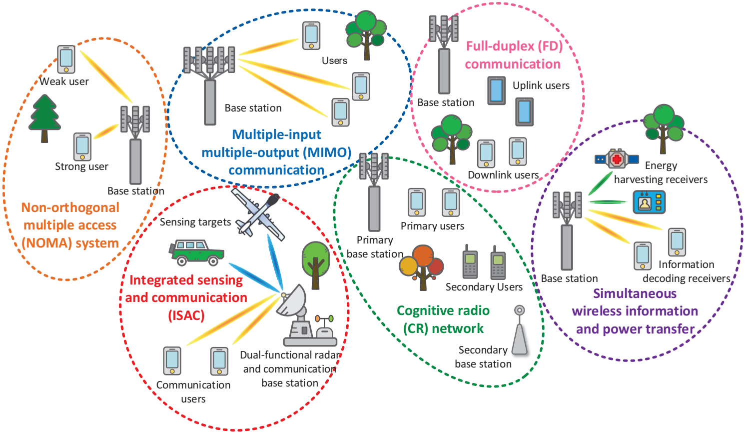
- **Numerous** devices
- **High** data rate
- **On-demand** services

New techniques to meet the requirements



⟹ **Resource allocation design** is needed

New techniques to meet the requirements



⟹ **Resource allocation design** is needed

Motivation

Resource allocation design

$$\underset{\mathrm{R}}{\text{maximize}} \;\; F(\mathrm{R} \mid \mathrm{H})$$

$F(\cdot \mid \cdot)$: **Performance metrics**, e.g., spectral efficiency, energy efficiency

R: **Wireless resources**, e.g., spectrum, power, time slot

H: **Radio propagation environment** including network geometry, path loss, fading, etc.

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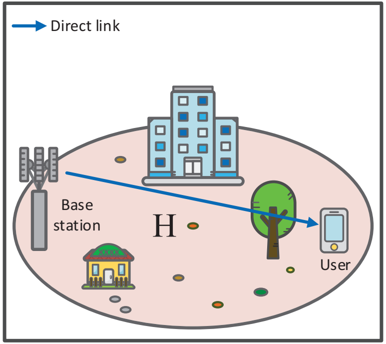

$\Longrightarrow$ Radio propagation environment is random

Motivation

Resource allocation design

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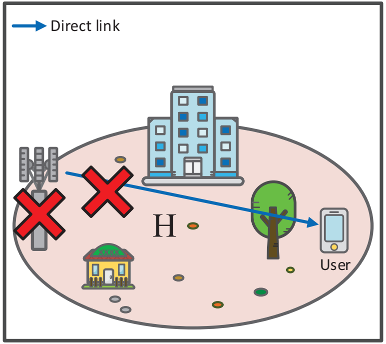

$\Longrightarrow$ Cannot ensure desired performance metrics

Motivation

Exploit **unmanned aerial vehicle (UAV)** and **intelligent reflecting surface (IRS)** to **customize** radio propagation environment H

$$\underset{\mathrm{R}}{\text{maximize}} \;\; F\left(\mathrm{R} \mid \mathrm{H}\right) \Rightarrow \underset{\mathrm{R},\mathrm{H}}{\text{maximize}} \;\; F\left(\mathrm{R}, \mathrm{H}\right)$$

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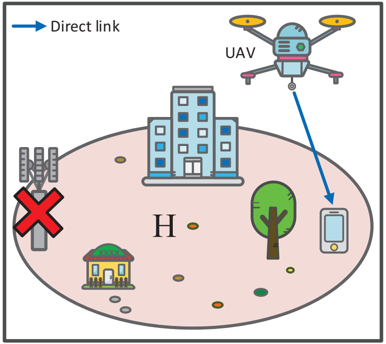
Exploit **unmanned aerial vehicle (UAV)** and **intelligent reflecting surface (IRS)** to **customize** radio propagation environment H

$$\underset{\mathrm{R}}{\text{maximize}} \;\; F\left(\mathrm{R} \mid \mathrm{H}\right) \Longrightarrow \underset{\mathrm{R,H}}{\text{maximize}} \;\; F\left(\mathrm{R}, \mathrm{H}\right)$$



[1] **D. Xu**, Y. Sun, D. W. K. Ng, and R. Schober, “Multiuser MISO UAV communications in uncertain environments with no-fly zones: robust trajectory and resource allocation design,” *IEEE Trans. Commun.*, vol. 68, no. 5, pp. 3153-3172, May 2020.

[2] **D. Xu**, Y. Sun, D. W. K. Ng, and R. Schober, “Robust resource allocation for UAV systems with UAV jittering and user location uncertainty,” in *Proc. IEEE Global Commun. Conf. Wkshps.*, Abu Dhabi, United Arab Emirates, Dec. 2018, pp. 1-6.

Motivation

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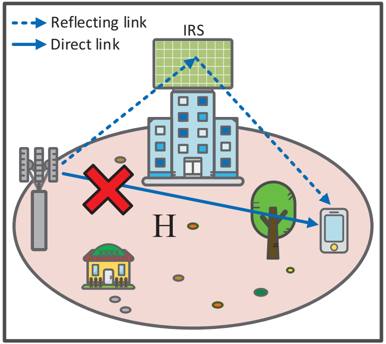

[1] **D. Xu**, X. Yu, Y. Sun, D. W. K. Ng, and R. Schober, “Resource allocation for IRS-assisted full-duplex cognitive radio systems,” *IEEE Trans. Commun.*, vol. 68, no. 12, pp. 7376-7394, Dec. 2020.

[2] **D. Xu**, V. Jamali, X. Yu, D. W. K. Ng, and R. Schober, “Optimal resource allocation design for large IRS-assisted SWIPT systems: A scalable optimization framework,” *IEEE Trans. Commun.*, vol. 70, no. 2, pp. 1423-1441, Feb. 2022.

[3] **D. Xu**, X. Yu, Y. Sun, D. W. K. Ng, and R. Schober, “Resource allocation for secure IRS-assisted multiuser MISO systems,” in *Proc. IEEE Global Commun. Conf. Wkshps.*, Waikoloa, HI, USA, Dec. 2019, pp. 1-6.

[4] **D. Xu**, X. Yu, and R. Schober, “Resource allocation for intelligent reflecting surface-assisted cognitive radio networks,” in *Proc. IEEE Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Atlanta, GA, USA, May 2020, pp. 1-5.

[5] **D. Xu**, X. Yu, V. Jamali, D. W. K. Ng, and R. Schober, “Resource allocation for large IRS-assisted SWIPT systems with non-linear energy harvesting model,” in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Nanjing, China, Mar. 2021, pp. 1-7.

[6] **D. Xu**, X. Yu, D. W. K. Ng, and R. Schober, “Resource allocation for active IRS-assisted multiuser communication systems,” in *Proc. Asilomar Conf. on Signals, Systems, and Computers*, Pacific Grove, CA, USA, Oct. 2021, pp. 113-119.

Outline

1. Introduction
2. Contributions
   - Resource Allocation Design for Unmanned Aerial Vehicle Communication
   - Resource Allocation Design for Intelligent Reflecting Surface-assisted Communication
3. Conclusion and Future Work

Unmanned Aerial Vehicle

- UAV: small aircraft operated by control station or equipped with algorithm-granted autonomy
  - **Modular** technology
  - **High** mobility
  - **Line-of-sight (LoS)** link

Wireless X Lab [1]

SoftBank Corporation [2]

Unmanned Aerial Vehicle

- UAV: small aircraft operated by control station or equipped with algorithm-granted autonomy
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- New challenges:
  - Limited battery capacity
  - Geometrical constraints for trajectory
  - Uncertain environment

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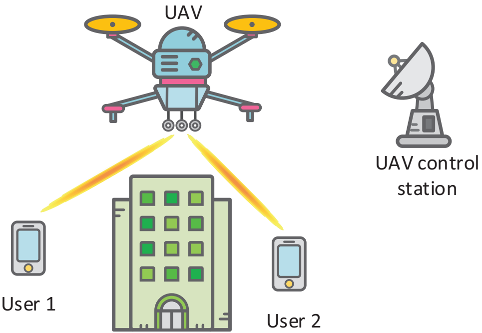
Contribution 1

Improve robustness of UAV communication in practical uncertain environments

D. Xu, Y. Sun, D. W. K. Ng, and R. Schober, “Multiuser MISO UAV communications in uncertain environments with no-fly zones: robust trajectory and resource allocation design,” *IEEE Trans. Commun.*, vol. 68, no. 5, pp. 3153-3172, May 2020.

Multiuser UAV Communications in Uncertain Environments with No-Fly Zones

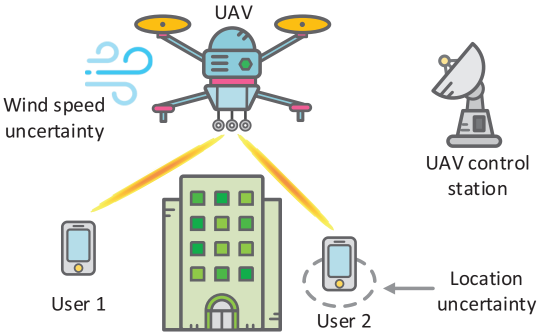
A rotary-wing UAV-mounted base station (BS) serves a few single-antenna users via LoS links



Multiuser UAV Communications in Uncertain Environments with No-Fly Zones

A rotary-wing UAV-mounted BS serves a few single-antenna users via LoS links

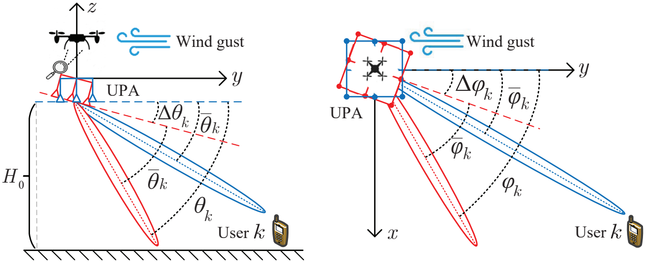
- User location uncertainty and wind speed uncertainty



Multiuser UAV Communications in Uncertain Environments with No-Fly Zones

A rotary-wing UAV-mounted BS serves a few single-antenna users via LoS links

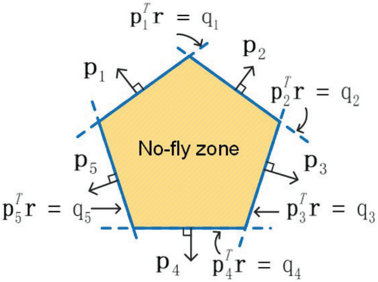
- User location uncertainty and wind speed uncertainty
- Wind-induced UAV body jittering



Multiuser UAV Communications in Uncertain Environments with No-Fly Zones

A rotary-wing UAV-mounted BS serves a few single-antenna users via LoS links

- User location uncertainty and wind speed uncertainty
- Wind-induced UAV body jittering
- Polygonal no-fly zone (NFZ)



Optimization Problem Formulation

Minimization of UAV total power consumption in each time slot

$$
\begin{array}{lll}
\underset{\mathbf{w}_k,\mathbf{r},\mathbf{v}_u}{\text{minimize}} & \eta\sum\limits_{k\in\mathscr{K}}\mathbf{w}_k^H\mathbf{w}_k + P_{\text{aero}}(\mathbf{v}_u) + M\cdot P_{\text{circ}} & \text{(UAV total power consumption)} \\
\text{s.t.} & \text{C1: } \left[\sum\limits_{k\in\mathscr{K}}\mathbf{w}_k\mathbf{w}_k^H\right]_{i,i} \leq P_i,\ \forall i, & \text{(per-antenna power constraint)} \\
 & \text{C2: } \Gamma_k(\mathbf{w}_k,\mathbf{r}) \geq \Gamma_{\text{req}_k}, \forall k, & \text{(quality-of-service constraint)} \\
 & \text{C3: } \|\mathbf{v}_u - \mathbf{v}_u[n-1]\| \leq a_{\max}\delta_T, & \text{(kinetic constraint)} \\
 & \text{C4: } \min\limits_{\mathbf{v}_w\in\Xi}\|\mathbf{v}_u+\mathbf{v}_w\|\,\delta_T \geq \|\mathbf{r}-\mathbf{r}[n-1]\|\,, & \text{(kinetic constraint)} \\
 & \text{C5: } \max\limits_{\mathbf{v}_w\in\Xi}\|\mathbf{v}_u+\mathbf{v}_w\| \leq V_g^{\max}, & \text{(safety constraint)} \\
 & \text{C6: } \bigwedge\limits_{j\in\mathscr{J}}\ \bigvee\limits_{i\in\mathcal{S}_j} Y_{ij}(\mathbf{r}) = 1. & \text{(NFZ constraint)}
\end{array}
$$

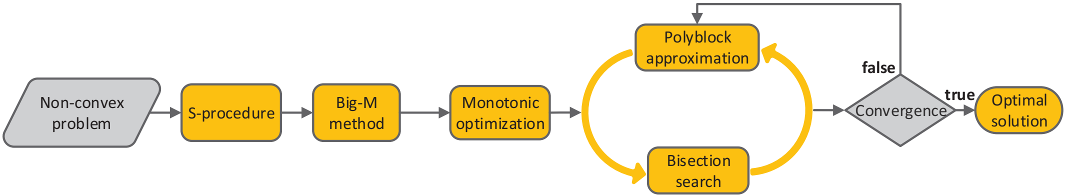
Optimization Problem Formulation

Minimization of UAV total power consumption in each time slot

$$
\begin{aligned}
\underset{\mathbf{w}_k,\mathbf{r},\mathbf{v}_u}{\text{minimize}} \quad & \eta \sum_{k\in\mathscr{K}} \mathbf{w}_k^H \mathbf{w}_k + P_{\text{aero}}(\mathbf{v}_u) + M \cdot P_{\text{circ}} \quad \text{(non-convex function)} \\
\text{s.t.} \quad & \text{C1: } \left[\sum_{k\in\mathscr{K}} \mathbf{w}_k \mathbf{w}_k^H\right]_{i,i} \leq P_i, \ \forall i, \\
& \text{C2: } \Gamma_k(\mathbf{w}_k, \mathbf{r}) \geq \Gamma_{\text{req}_k}, \forall k, \quad \text{(non-convex constraint)} \\
& \text{C3: } \|\mathbf{v}_u - \mathbf{v}_u[n-1]\| \leq a_{\max}\delta_T, \\
& \text{C4: } \min_{\mathbf{v}_w\in\Xi} \|\mathbf{v}_u + \mathbf{v}_w\| \, \delta_T \geq \|\mathbf{r} - \mathbf{r}[n-1]\|, \quad \text{(semi-infinite constraint)} \\
& \text{C5: } \max_{\mathbf{v}_w\in\Xi} \|\mathbf{v}_u + \mathbf{v}_w\| \leq V_g^{\max}, \quad \text{(semi-infinite constraint)} \\
& \text{C6: } \bigwedge_{j\in\mathscr{J}} \bigvee_{i\in\mathscr{S}_j} Y_{ij}(\mathbf{r}) = 1. \quad \text{(disjunctive constraint)}
\end{aligned}
$$

Convex optimization problems can be solved **efficiently** and **optimally**; however, this problem is non-convex

Flow Chart of the Developed Algorithms – Optimal Scheme



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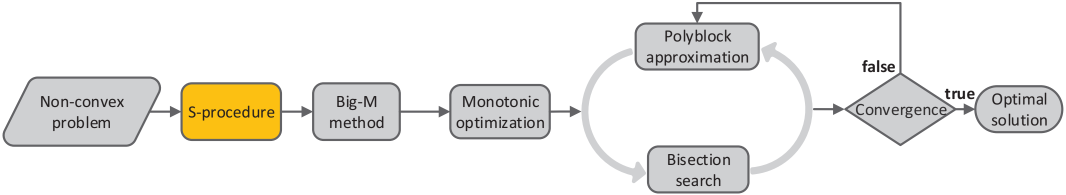


Lemma 1: S-Procedure

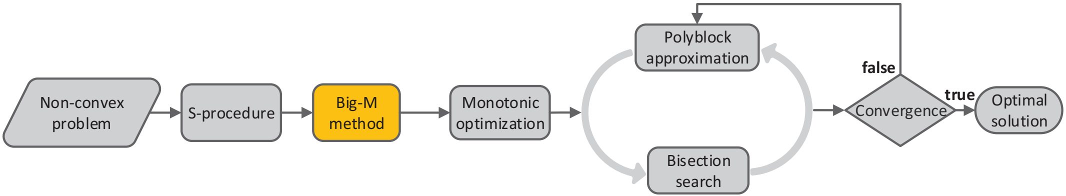
Given a function $f_m(\mathbf{x}) = \mathbf{x}^H \mathbf{B}_m \mathbf{x} + 2\mathrm{Re}\left\{\mathbf{b}_m^H \mathbf{x}\right\} + b_m$, $m \in \{1,2\}$, $\mathbf{x} \in \mathbb{C}^{N\times 1}$, $\mathbf{B}_m \in \mathbb{H}^N$, $\mathbf{b}_m \in \mathbb{C}^{N\times 1}$, and $\mathrm{b}_m \in \mathbb{R}^{1\times 1}$. Then, the implication $f_1(\mathbf{x}) \leq 0 \Rightarrow f_2(\mathbf{x}) \leq 0$ holds if and only if there exists a $\delta \geq 0$ such that

$$\delta \begin{bmatrix} \mathbf{B}_1 & \mathbf{b}_1 \\ \mathbf{b}_1^H & b_1 \end{bmatrix} - \begin{bmatrix} \mathbf{B}_2 & \mathbf{b}_2 \\ \mathbf{b}_2^H & b_2 \end{bmatrix} \succeq \mathbf{0},$$

provided that there exists a point $\widehat{\mathbf{x}}$ such that $f_m(\widehat{\mathbf{x}}) < 0$.

$\Longrightarrow$ Recast semi-infinite constraints C4 and C5 into convex linear matrix inequalities

Flow Chart of the Developed Algorithms – Optimal Scheme



Theorem 1

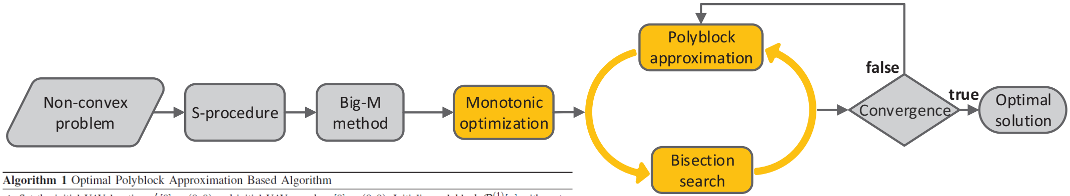
The disjunctive programming in constraint C6 is equivalent to the following mixed integer linear programming:

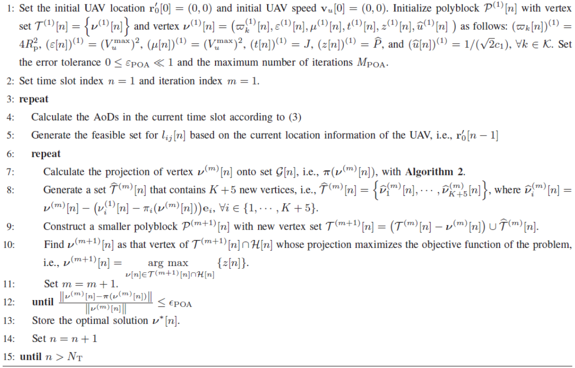
$$\mathbf{p}_{ij}^T \mathbf{r} - q_{ij} + G l_{ij} \geq 0, \ \ \forall i, \ \ \forall j,$$

if there exists at least one binary variable $l_{ij} \in \{0, 1\}$ satisfies $l_{ij} = 0$, and G is a sufficiently large constant.

$\Longrightarrow$ Recast disjunctive constraint C6 into a binary linear constraint

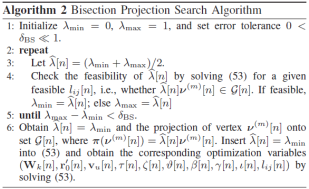
Flow Chart of the Developed Algorithms – Optimal Scheme





Algorithm 1 Optimal Polyblock Approximation Based Algorithm

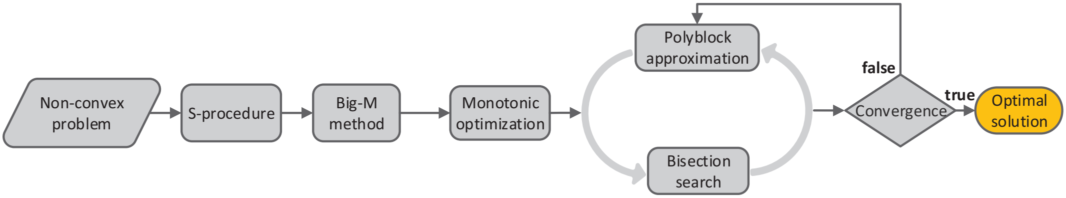
```
Set the initial UAV location $\mathbf{r}_0'[0] = (0,0)$ and initial UAV speed $\mathbf{v}_u[0] = (0,0)$. Initialize polyblock $\mathcal{P}^{(1)}[n]$ with vertex set $\mathcal{T}^{(1)}[n] = \left\{\boldsymbol{\nu}^{(1)}[n]\right\}$ and vertex $\boldsymbol{\nu}^{(1)}[n] = \left(\varpi_k^{(1)}[n], \varepsilon^{(1)}[n], \mu^{(1)}[n], t^{(1)}[n], z^{(1)}[n], \widehat{u}^{(1)}[n]\right)$ as follows: $(\varpi_k[n])^{(1)} = 4R_{\mathrm{p}}^2$, $(\varepsilon[n])^{(1)} = (V_u^{\max})^2$, $(\mu[n])^{(1)} = (V_u^{\max})^2$, $(t[n])^{(1)} = J$, $(z[n])^{(1)} = \widehat{P}$, and $(\widehat{u}[n])^{(1)} = 1/(\sqrt{2}c_1)$, $\forall k \in \mathcal{K}$. Set the error tolerance $0 \leq \varepsilon_{\mathrm{POA}} \ll 1$ and the maximum number of iterations $M_{\mathrm{POA}}$.
Set time slot index $n = 1$ and iteration index $m = 1$.
repeat
    Calculate the AoDs in the current time slot according to (3)
    Generate the feasible set for $l_{ij}[n]$ based on the current location information of the UAV, i.e., $\mathbf{r}_0'[n-1]$
    repeat
        Calculate the projection of vertex $\boldsymbol{\nu}^{(m)}[n]$ onto set $\mathcal{G}[n]$, i.e., $\boldsymbol{\pi}(\boldsymbol{\nu}^{(m)}[n])$, with Algorithm 2.
        Generate a set $\widehat{\mathcal{T}}^{(m)}[n]$ that contains $K+5$ new vertices, i.e., $\widehat{\mathcal{T}}^{(m)}[n] = \left\{\widehat{\boldsymbol{\nu}}_1^{(m)}[n], \cdots, \widehat{\boldsymbol{\nu}}_{K+5}^{(m)}[n]\right\}$, where $\widehat{\boldsymbol{\nu}}_i^{(m)}[n] = \boldsymbol{\nu}^{(m)}[n] - \left(\nu_i^{(1)}[n] - \pi_i(\boldsymbol{\nu}^{(m)}[n])\right)\mathbf{e}_i$, $\forall i \in \{1, \cdots, K+5\}$.
        Construct a smaller polyblock $\mathcal{P}^{(m+1)}[n]$ with new vertex set $\mathcal{T}^{(m+1)}[n] = \left(\mathcal{T}^{(m)}[n] - \boldsymbol{\nu}^{(m)}[n]\right) \cup \widehat{\mathcal{T}}^{(m)}[n]$.
        Find $\boldsymbol{\nu}^{(m+1)}[n]$ as that vertex of $\mathcal{T}^{(m+1)}[n] \cap \mathcal{H}[n]$ whose projection maximizes the objective function of the problem, i.e., $\boldsymbol{\nu}^{(m+1)}[n] = \underset{\boldsymbol{\nu}[n] \in \mathcal{T}^{(m+1)}[n] \cap \mathcal{H}[n]}{\arg\max} \{z[n]\}$.
        Set $m = m + 1$.
    until $\frac{\left\|\boldsymbol{\nu}^{(m)}[n] - \boldsymbol{\pi}(\boldsymbol{\nu}^{(m)}[n])\right\|}{\left\|\boldsymbol{\nu}^{(m)}[n]\right\|} \leq \epsilon_{\mathrm{POA}}$
    Store the optimal solution $\boldsymbol{\nu}^*[n]$.
    Set $n = n + 1$
until $n > N_{\mathrm{T}}$
```



Algorithm 2 Bisection Projection Search Algorithm

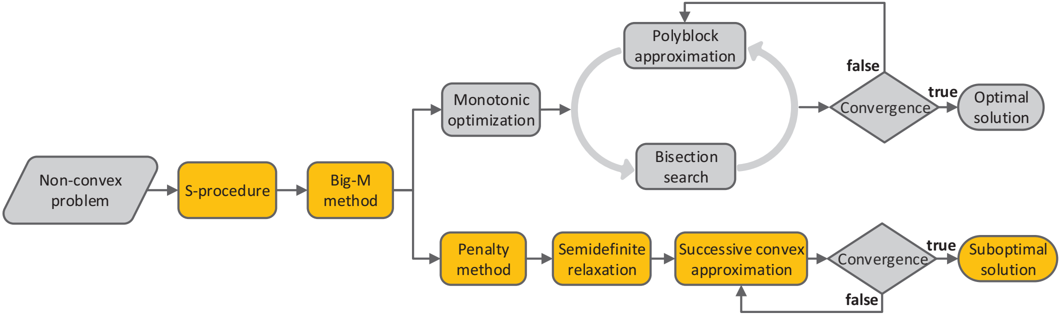
```
Initialize $\lambda_{\min} = 0$, $\lambda_{\max} = 1$, and set error tolerance $0 < \delta_{\mathrm{BS}} \ll 1$.
repeat
    Let $\widehat{\lambda}[n] = (\lambda_{\min} + \lambda_{\max})/2$.
    Check the feasibility of $\widehat{\lambda}[n]$ by solving (53) for a given feasible $l_{ij}[n]$, i.e., whether $\widehat{\lambda}[n]\boldsymbol{\nu}^{(m)}[n] \in \mathcal{G}[n]$. If feasible, $\lambda_{\min} = \widehat{\lambda}[n]$; else $\lambda_{\max} = \widehat{\lambda}[n]$
until $\lambda_{\max} - \lambda_{\min} < \delta_{\mathrm{BS}}$.
Obtain $\widehat{\lambda}[n] = \lambda_{\min}$ and the projection of vertex $\boldsymbol{\nu}^{(m)}[n]$ onto set $\mathcal{G}[n]$, where $\boldsymbol{\pi}(\boldsymbol{\nu}^{(m)}[n]) = \widehat{\lambda}[n]\boldsymbol{\nu}^{(m)}[n]$. Insert $\widehat{\lambda}[n] = \lambda_{\min}$ into (53) and obtain the corresponding optimization variables $(\mathbf{W}_k[n], \mathbf{r}_0'[n], \mathbf{v}_u[n], \tau[n], \zeta[n], \vartheta[n], \beta[n], \gamma[n], \iota[n], l_{ij}[n])$ by solving (53).
```

Flow Chart of the Developed Algorithms – Optimal Scheme



- Reveal system **performance upper bound**
- **Benchmark** for any suboptimal schemes
- High complexity, time-consuming

Flow Chart of the Developed Algorithms – Suboptimal Scheme



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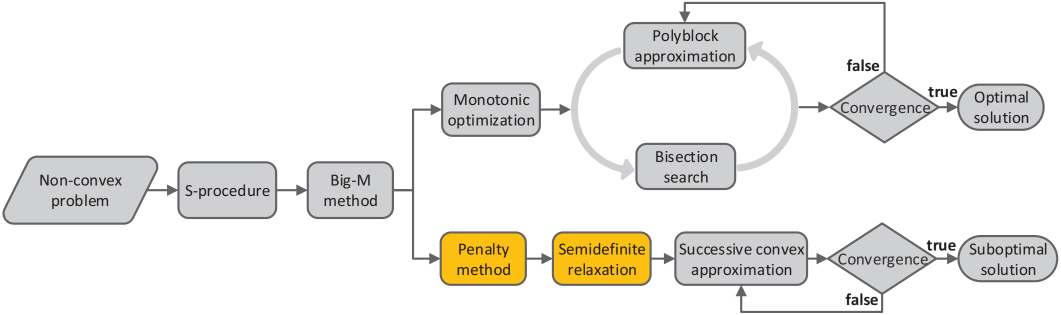


Non-convex problem

S-procedure

Big-M method

Monotonic optimization

Polyblock approximation

Bisection search

Convergence

false

true

Optimal solution

Penalty method

Semidefinite relaxation

Successive convex approximation

Convergence

true

false

Suboptimal solution

Theorem 2

The original problem can be equivalently recast as follows

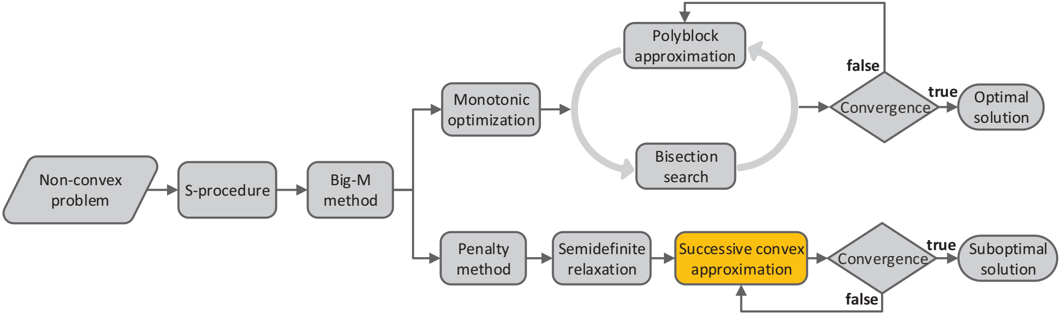
$$\begin{aligned} \underset{\substack{\mathbf{W}_k,\mathbf{r},\mathbf{v}_{\mathrm{U}},\\ l_{ij},\mathcal{A},\hat{\mathbf{u}},g}}{\text{minimize}} \quad & \sum_{k\in\mathcal{K}} \mathrm{Tr}(\mathbf{W}_k) + g + \chi \sum_{j\in\mathcal{J}} \sum_{i\in S_j} (l_{ij} - l_{ij}^2) \\ \text{s.t.} \quad & \text{C1-C7b}, \text{C8-C13}, \end{aligned}$$

if χ is a sufficiently large constant that penalizes the objective function for any l_{ij} not equal to 0 or 1.

Theorem 3

If the required signal-to-interference-plus-noise ratio of user k, i.e., $\Gamma_{\mathrm{req}_k} > 0$, a rank-one beamforming matrix $\mathbf{W}_k$ can always be obtained.

Flow Chart of the Developed Algorithms – Suboptimal Scheme



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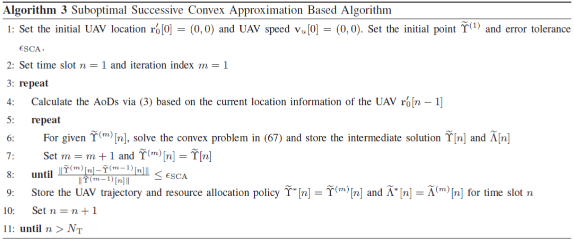
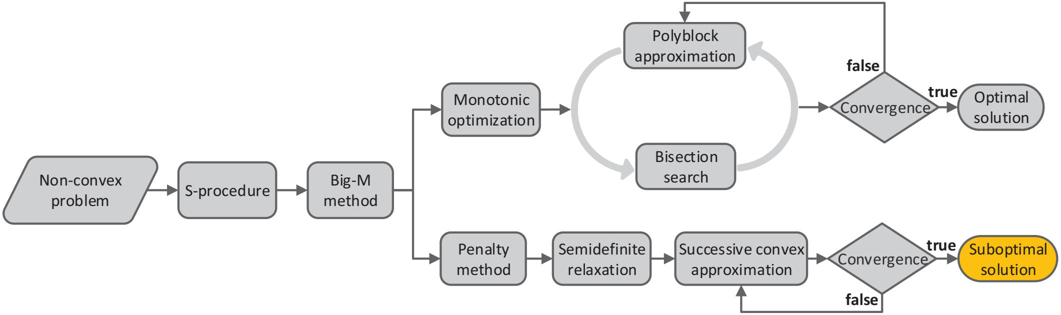


Algorithm 3 Suboptimal Successive Convex Approximation Based Algorithm

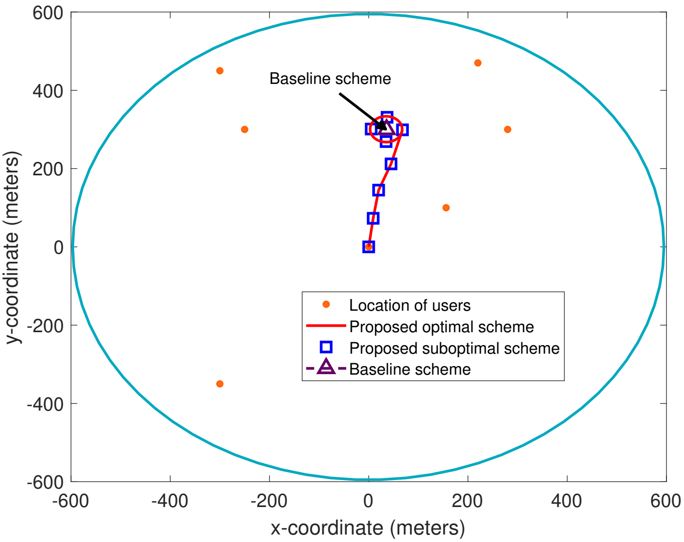
```
Set the initial UAV location $\mathbf{r}'_0[0] = (0,0)$ and UAV speed $\mathbf{v}_u[0] = (0,0)$. Set the initial point $\widetilde{\Upsilon}^{(1)}$ and error tolerance $\epsilon_{\mathrm{SCA}}$.
Set time slot $n = 1$ and iteration index $m = 1$
repeat
    Calculate the AoDs via (3) based on the current location information of the UAV $\mathbf{r}'_0[n-1]$
    repeat
        For given $\widetilde{\Upsilon}^{(m)}[n]$, solve the convex problem in (67) and store the intermediate solution $\widetilde{\Upsilon}[n]$ and $\widetilde{\Lambda}[n]$
        Set $m = m + 1$ and $\widetilde{\Upsilon}^{(m)}[n] = \widetilde{\Upsilon}[n]$
    until $\frac{\|\widetilde{\Upsilon}^{(m)}[n]-\widetilde{\Upsilon}^{(m-1)}[n]\|}{\|\widetilde{\Upsilon}^{(m-1)}[n]\|} \le \epsilon_{\mathrm{SCA}}$
    Store the UAV trajectory and resource allocation policy $\widetilde{\Upsilon}^*[n] = \widetilde{\Upsilon}^{(m)}[n]$ and $\widetilde{\Lambda}^*[n] = \widetilde{\Lambda}^{(m)}[n]$ for time slot $n$
    Set $n = n + 1$
until $n > N_{\mathrm{T}}$
```

Flow Chart of the Developed Algorithms – Suboptimal Scheme



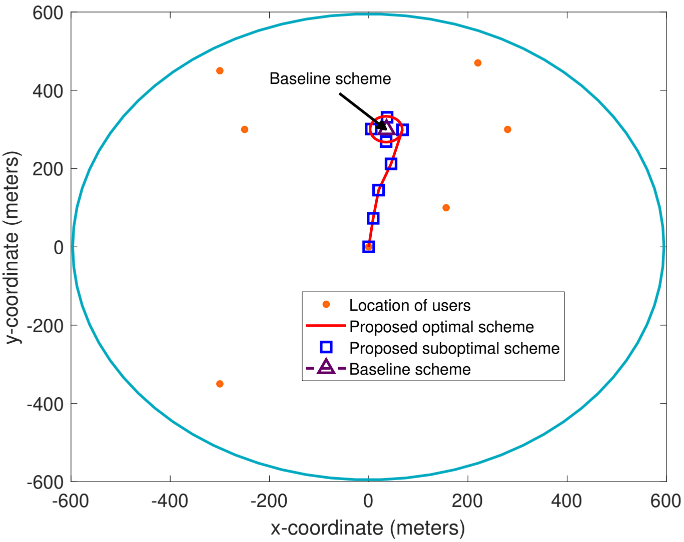
- **Low complexity**, computationally-efficient
- Slight performance loss compared to optimal scheme

Simulation Results: UAV Trajectory

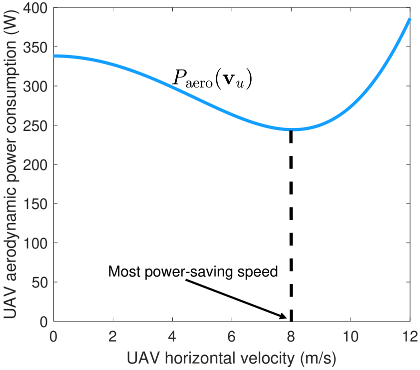


- Without wind and NFZs
- **Baseline scheme**: UAV hovers at the optimal position and employs the optimal beamforming policy

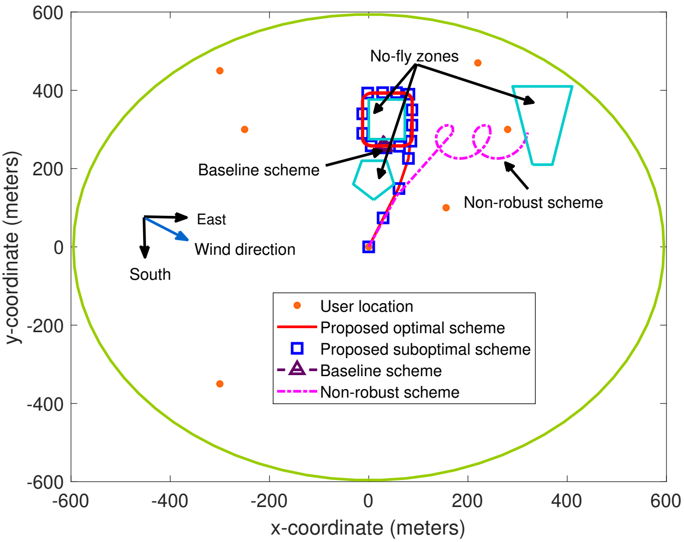
Simulation Results: UAV Trajectory



Hovering is not the most energy-saving

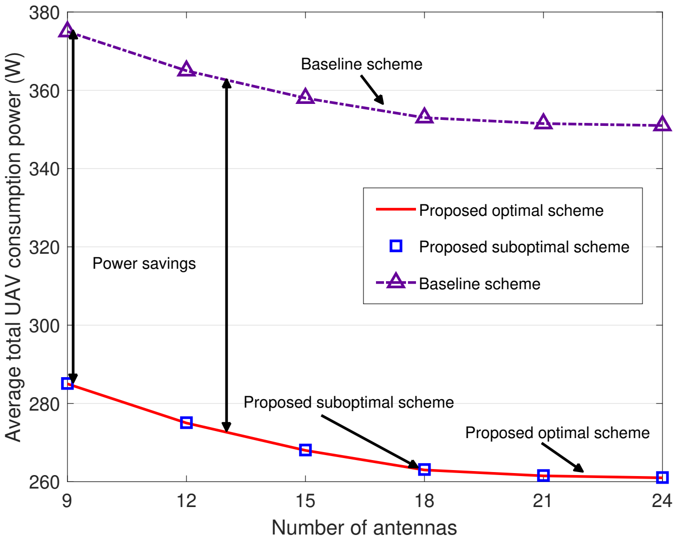


Simulation Results: UAV Trajectory



- With wind and NFZs
- **Baseline scheme**: UAV hovers at the optimal position and employs the optimal beamforming policy
- **Non-robust scheme**: Do not take into account wind and NFZs

Simulation Results: Total Power Consumption

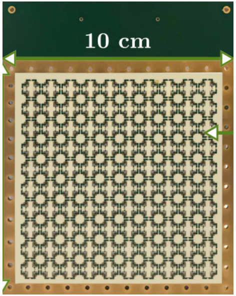


- With wind and NFZs
- **Baseline scheme**: UAV hovers at the optimal position and employs the optimal beamforming policy

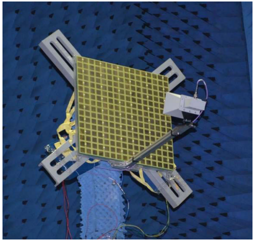
Outline

IRS

- IRS: planar surface comprises a group of low-cost passive elements and each element can adjust the phase of incident signals
  - **Reconfigure** radio propagation environment
  - **Low** power consumption



[3]



[4]

IRS

- IRS: planar surface comprises a group of low-cost passive elements and each element can adjust the phase of incident signals
  - **Reconfigure** radio propagation environment
  - **Low** power consumption

- New challenges:
  - Non-convex unit-modulus constraint
  - Coupled with other design variables

IRS

- IRS: planar surface comprises a group of low-cost passive elements and each element can adjust the phase of incident signals
  - **Reconfigure** radio propagation environment
  - **Low** power consumption

- New challenges:
  - Non-convex unit-modulus constraint
  - Coupled with other design variables

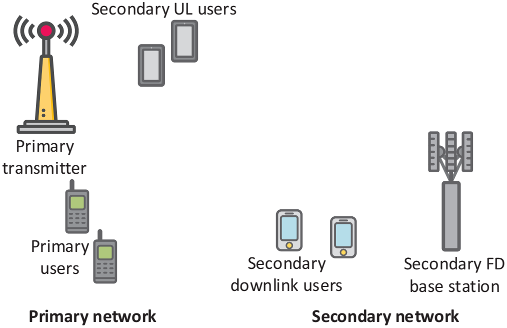
Contribution 2

Exploit IRS to improve the performance of full-duplex (FD) cognitive radio (CR) networks

D. Xu, X. Yu, Y. Sun, D. W. K. Ng, and R. Schober, "Resource allocation for IRS-assisted full-duplex cognitive radio systems," *IEEE Trans. Commun.*, vol. 68, no. 12, pp. 7376-7394, Dec. 2020.

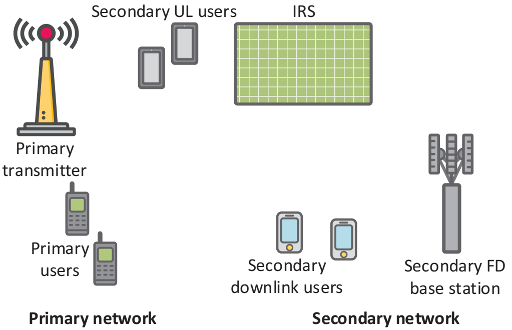
IRS-assisted Full-duplex Cognitive Radio Systems

- A primary network contains a primary transmitter and a set of primary users
- A secondary network contains an FD BS and a set of uplink and downlink users



IRS-assisted Full-duplex Cognitive Radio Systems

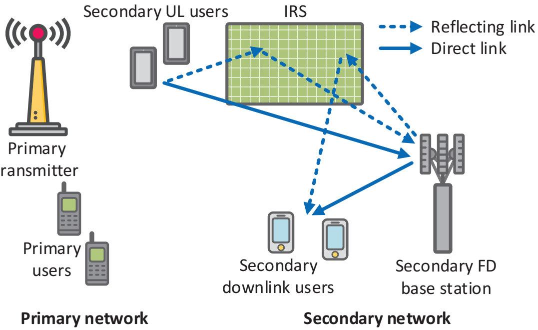
Deploy an IRS in the considered system to



IRS-assisted Full-duplex Cognitive Radio Systems

Deploy an IRS in the considered system to

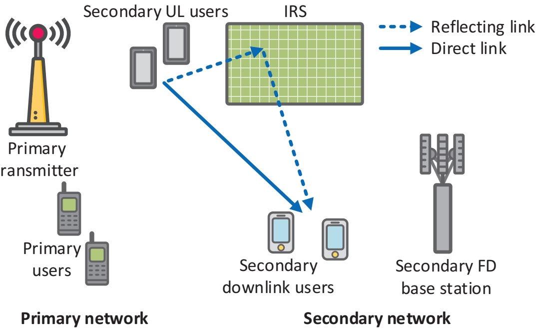
- Facilitate information transmission of secondary network



IRS-assisted Full-duplex Cognitive Radio Systems

Deploy an IRS in the considered system to

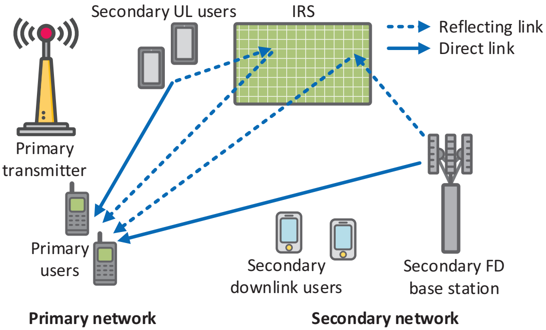
- Facilitate information transmission of secondary network
- Suppress co-channel interference in secondary network



IRS-assisted Full-duplex Cognitive Radio Systems

Deploy an IRS in the considered system to

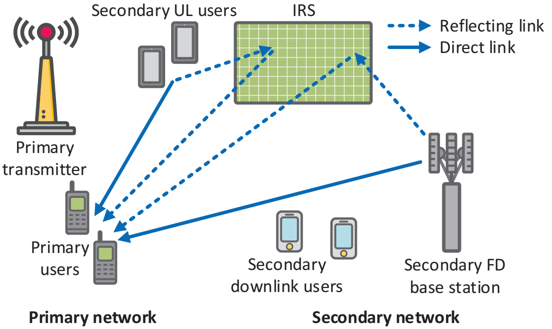
- Facilitate information transmission of secondary network
- Suppress co-channel interference in secondary network
- Alleviate interference from secondary network to primary users



IRS-assisted Full-duplex Cognitive Radio Systems

Deploy an IRS in the considered system to

- Facilitate information transmission of secondary network
- Suppress co-channel interference in secondary network
- Alleviate interference from secondary network to primary users
- Model the channel uncertainty for the links between secondary network and primary users



Optimization Problem Formulation

Maximization of secondary network spectral efficiency

$$\underset{\mathbf{w}_k,\mathbf{v}_j,p_j,\mathbf{\Psi}}{\text{maximize}} \quad \sum_{j\in\mathcal{J}} R_j^{\mathrm{UL}}(\mathbf{w}_k,\mathbf{v}_j,p_j,\mathbf{\Psi}) + \sum_{k\in\mathcal{K}} R_k^{\mathrm{DL}}(\mathbf{w}_k,p_j,\mathbf{\Psi}) \quad \text{(spectral efficiency)}$$

$$\text{s.t.} \quad \text{C1: } \sum_{k\in\mathcal{K}} \|\mathbf{w}_k\|^2 \leq P_{\max}^{\mathrm{DL}}, \quad \text{(secondary BS power constraint)}$$

$$\text{C2: } 0 \leq p_j \leq p_{j,\max}, \ \forall j, \quad \text{(uplink user power constraint)}$$

$$\text{C3: } \mathbf{\Psi} = \mathrm{diag}\left(e^{j\psi_1},\cdots,e^{j\psi_M}\right), \quad \text{(IRS unit-modulus constraint)}$$

$$\text{C4: } \max_{\substack{\mathbf{l}_{\mathrm{D},i}\in\Omega_{\mathrm{D},i}\\ \mathbf{l}_{\mathrm{R},i}\in\Omega_{\mathrm{R},i}\\ e_{i,j}\in\Omega_{i,j}}} I_i(\mathbf{w}_k,p_j,\mathbf{\Psi}) \leq p_{\mathrm{tol}_i}, \ \forall i. \quad \text{(interference leakage constraint)}$$

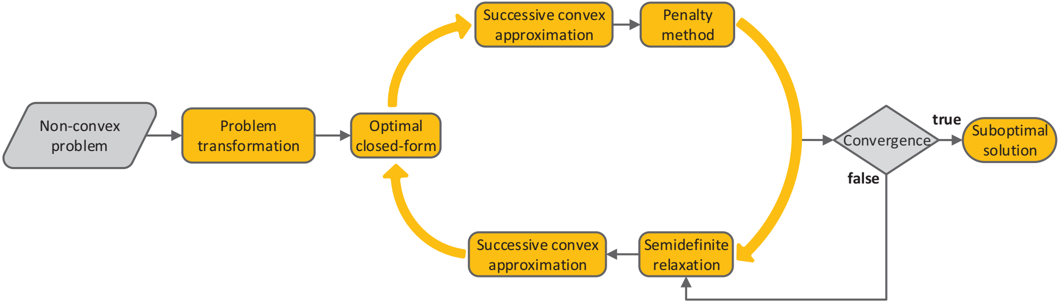
Optimization Problem Formulation

Maximization of secondary network spectral efficiency

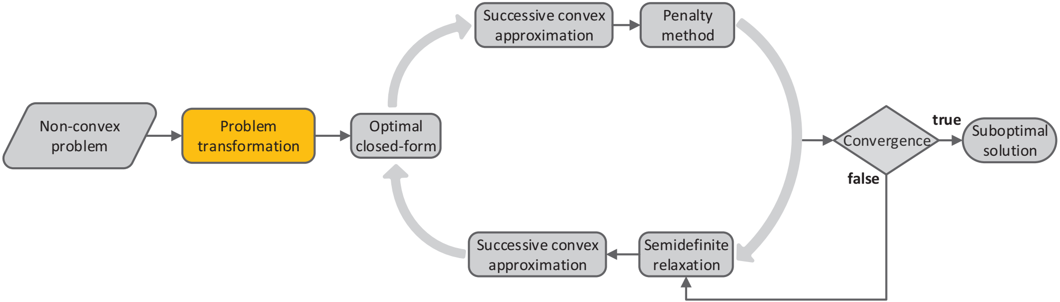
$$\begin{aligned}
\underset{\mathbf{w}_k, \mathbf{v}_j, p_j, \boldsymbol{\Psi}}{\text{maximize}} \quad & \sum_{j \in \mathcal{J}} R_j^{\mathrm{UL}}(\mathbf{w}_k, \mathbf{v}_j, p_j, \boldsymbol{\Psi}) + \sum_{k \in \mathcal{K}} R_k^{\mathrm{DL}}(\mathbf{w}_k, p_j, \boldsymbol{\Psi}) \quad \text{(non-convex function)} \\
\text{s.t.} \quad & \text{C1: } \sum_{k \in \mathcal{K}} \|\mathbf{w}_k\|^2 \leq P_{\max}^{\mathrm{DL}}, \\
& \text{C2: } 0 \leq p_j \leq p_{j,\max}, \ \forall j, \\
& \text{C3: } \boldsymbol{\Psi} = \mathrm{diag}\left(e^{j\psi_1}, \cdots, e^{j\psi_M}\right), \quad \text{(non-convex constraint)} \\
& \text{C4: } \max_{\substack{\mathbf{l}_{\mathrm{D},i} \in \Omega_{\mathrm{D},i} \\ \mathbf{l}_{\mathrm{R},i} \in \Omega_{\mathrm{R},i} \\ e_{i,j} \in \Omega_{i,j}}} I_i(\mathbf{w}_k, p_j, \boldsymbol{\Psi}) \leq p_{\mathrm{tol}_i}, \ \forall i. \quad \text{(semi-infinite constraint)}
\end{aligned}$$

Optimal solution is **challenging** to obtain due to non-convexity and coupled variables

Flow Chart of the Developed Scheme



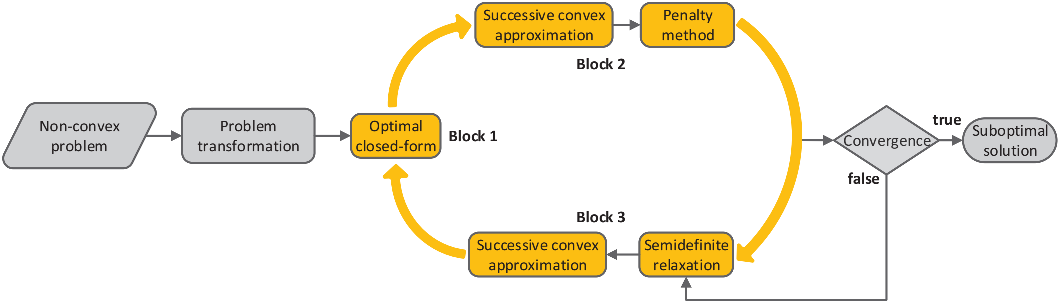
Flow Chart of the Developed Scheme



- Exploit Schwarz inequality and Minkowski inequality
- Employ S-procedure

$\Longrightarrow$ Rewrite semi-infinite constraint C4 as a **tractable** constraint

Flow Chart of the Developed Scheme



- Exploit block coordinate descent theory and divide coupled variables into three blocks:

  Block 1: $\{\mathbf{v}_j\}$

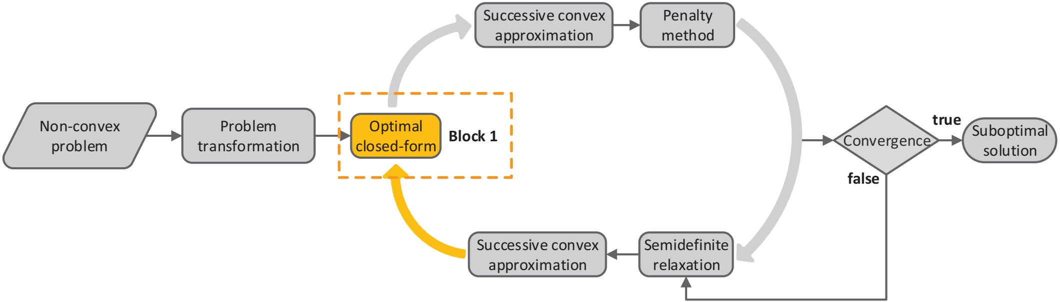
  Block 2: $\{\mathbf{\Psi}\}$

  Block 3: $\{\mathbf{w}_k, p_j\}$

- Each block is associated with a subproblem, solve one subproblem with **the other two Blocks fixed**

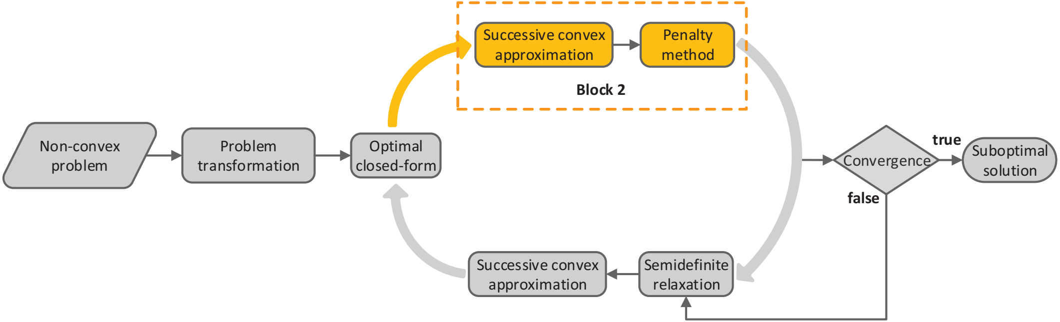
$\Longrightarrow$ **Circumvent** variable coupling issue

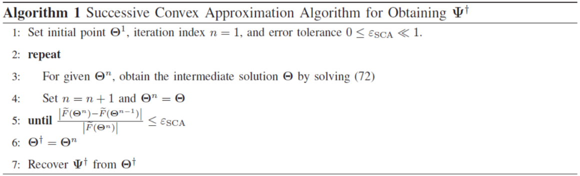
Flow Chart of the Developed Scheme



Fixing Blocks 2 and 3 results in a **convex** problem $\Longrightarrow$ Obtain the **optimal** solution for Block 1

Flow Chart of the Developed Scheme





Algorithm 1 Successive Convex Approximation Algorithm for Obtaining $\boldsymbol{\Psi}^{\dagger}$

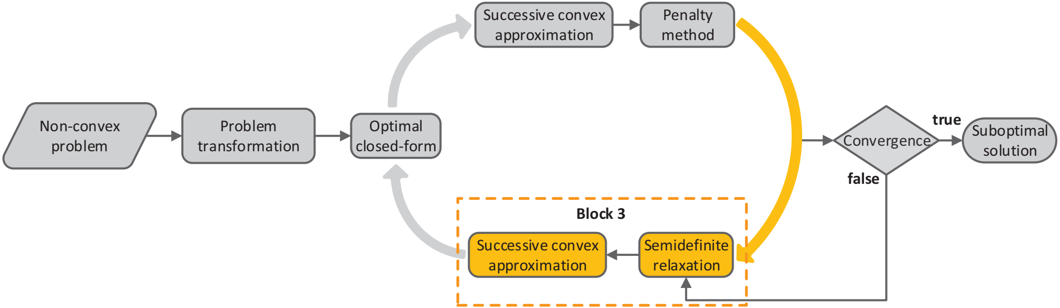
```
Set initial point $\boldsymbol{\Theta}^1$, iteration index $n = 1$, and error tolerance $0 \leq \varepsilon_{\mathrm{SCA}} \ll 1$.
repeat
    For given $\boldsymbol{\Theta}^n$, obtain the intermediate solution $\boldsymbol{\Theta}$ by solving (72)
    Set $n = n + 1$ and $\boldsymbol{\Theta}^n = \boldsymbol{\Theta}$
until $\frac{|\widetilde{F}(\boldsymbol{\Theta}^n) - \widetilde{F}(\boldsymbol{\Theta}^{n-1})|}{|\widetilde{F}(\boldsymbol{\Theta}^n)|} \leq \varepsilon_{\mathrm{SCA}}$
$\boldsymbol{\Theta}^{\dagger} = \boldsymbol{\Theta}^n$
Recover $\boldsymbol{\Psi}^{\dagger}$ from $\boldsymbol{\Theta}^{\dagger}$
```

Theorem 4

Denote the optimal solution of the reformulated problem as $\boldsymbol{\Theta}_q$ with penalty factor χ_q. When χ_q is sufficiently large, i.e., $\chi_q \to \infty$, every limit point $\overline{\boldsymbol{\Theta}}$ of the sequence $\{\boldsymbol{\Theta}_q\}$ is an optimal solution of the original problem.

$\Longrightarrow$ Obtain a **suboptimal** solution for Block 2

Flow Chart of the Developed Scheme



Non-convex problem

Problem transformation

Optimal closed-form

Successive convex approximation

Penalty method

Convergence

true

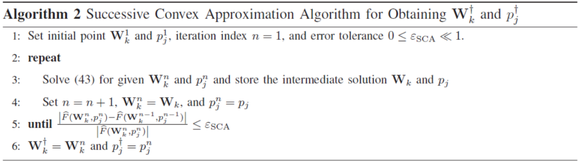
Suboptimal solution

false

Block 3

Successive convex approximation

Semidefinite relaxation

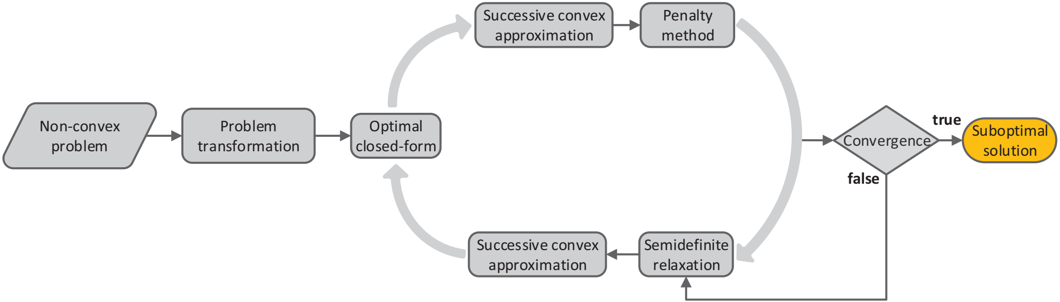


Algorithm 2 Successive Convex Approximation Algorithm for Obtaining $\mathbf{W}_k^{\dagger}$ and $p_j^{\dagger}$

```
Set initial point $\mathbf{W}_k^1$ and $p_j^1$, iteration index $n = 1$, and error tolerance $0 \leq \varepsilon_{\mathrm{SCA}} \ll 1$.
repeat
    Solve (43) for given $\mathbf{W}_k^n$ and $p_j^n$ and store the intermediate solution $\mathbf{W}_k$ and $p_j$
    Set $n = n + 1$, $\mathbf{W}_k^n = \mathbf{W}_k$, and $p_j^n = p_j$
until $\frac{|\widehat{F}(\mathbf{W}_k^n, p_j^n) - \widehat{F}(\mathbf{W}_k^{n-1}, p_j^{n-1})|}{|\widehat{F}(\mathbf{W}_k^n, p_j^n)|} \leq \varepsilon_{\mathrm{SCA}}$
$\mathbf{W}_k^{\dagger} = \mathbf{W}_k^n$ and $p_j^{\dagger} = p_j^n$
```

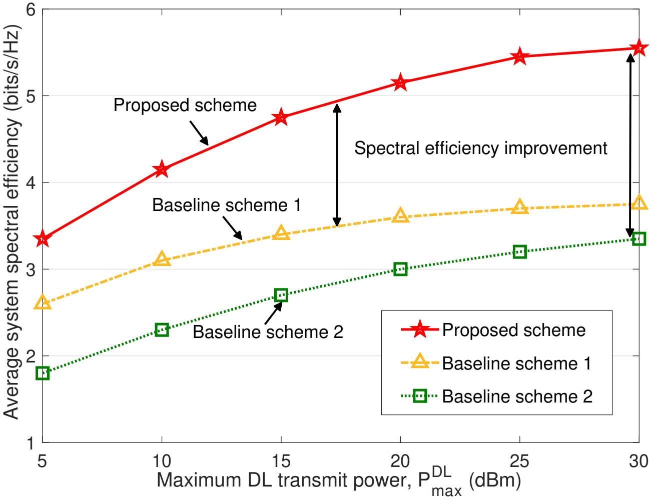
$\Longrightarrow$ Obtain a **suboptimal** solution for Block 3

Flow Chart of the Developed Scheme



- **Low complexity**, computationally-efficient
- **Guaranteed** convergence
- **General** framework for IRS design

Simulation Results: Secondary Network Spectral Efficiency



- 8 antennas, 8 IRS elements, 3 uplink users, 2 downlink users, and 2 primary users
- **Baseline scheme 1**: FD CR network does not employ IRS
- **Baseline scheme 2**: Secondary BS operates in the half-duplex mode

Outline

1. Introduction
2. Contributions
3. Conclusion and Future Work

Conclusion

- UAVs and IRSs are promising solutions to **customize** wireless channels to enhance performance of future wireless networks
- System designers should take into account **practical issues** when exploiting UAVs and IRSs in conventional communication systems
- **Resource allocation design** is a key means to unleash the potentials of UAVs and IRSs
- Both **optimal** and **suboptimal** resource allocation schemes are crucial for practical communication systems design

Future Work

- Optimization framework design for swarm UAV systems
- Optimization framework design for multi-functional IRSs
- Optimal algorithm design for practical IRS-assisted networks

During the doctoral program, I have published the following papers as first author.

Journal Publications:

[1] **D. Xu**, Y. Sun, D. W. K. Ng, and R. Schober, “Multiuser MISO UAV communications in uncertain environments with no-fly zones: robust trajectory and resource allocation design,” *IEEE Trans. Commun.*, vol. 68, no. 5, pp. 3153-3172, May 2020.

[2] **D. Xu**, X. Yu, Y. Sun, D. W. K. Ng, and R. Schober, “Resource allocation for IRS-assisted full-duplex cognitive radio systems,” *IEEE Trans. Commun.*, vol. 68, no. 12, pp. 7376-7394, Dec. 2020.

[3] **D. Xu**, V. Jamali, X. Yu, D. W. K. Ng, and R. Schober, “Optimal resource allocation design for large IRS-assisted SWIPT systems: A scalable optimization framework,” *IEEE Trans. Commun.*, vol. 70, no. 2, pp. 1423-1441, Feb. 2022.

[4] **D. Xu**, X. Yu, D. W. K. Ng, A. Schmeink and R. Schober, “Robust and Secure Resource Allocation for ISAC Systems: A Novel Optimization Framework for Variable-Length Snapshots,” *IEEE Trans. Commun.*, vol. 70, no. 12, pp. 8196-8214, Dec. 2022.

Conference Publications:

[1] **D. Xu**, Y. Sun, D. W. K. Ng, and R. Schober, “Robust resource allocation for UAV systems with UAV jittering and user location uncertainty,” in *Proc. IEEE Global Commun. Conf. Wkshps.*, Abu Dhabi, United Arab Emirates, Dec. 2018, pp. 1-6.

[2] **D. Xu**, X. Yu, Y. Sun, D. W. K. Ng, and R. Schober, “Resource allocation for secure IRS-assisted multiuser MISO systems,” in *Proc. IEEE Global Commun. Conf. Wkshps.*, Waikoloa, HI, USA, Dec. 2019, pp. 1-6.

[3] **D. Xu**, X. Yu, and R. Schober, “Resource allocation for intelligent reflecting surface-assisted cognitive radio networks,” in *Proc. IEEE Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Atlanta, GA, USA, May 2020, pp. 1-5.

[4] **D. Xu**, X. Yu, V. Jamali, D. W. K. Ng, and R. Schober, “Resource allocation for large IRS-assisted SWIPT systems with non-linear energy harvesting model,” in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Nanjing, China, Mar. 2021, pp. 1-7.

[5] **D. Xu**, X. Yu, D. W. K. Ng, and R. Schober, “Resource allocation for active IRS-assisted multiuser communication systems,” in *Proc. Asilomar Conf. on Signals, Systems, and Computers*, Pacific Grove, CA, USA, Oct. 2021, pp. 113-119.

During the doctoral program, I have contributed to the following papers.

Journal Publications:

[1] Y. Sun, **D. Xu**, D. W. K. Ng, L. Dai, and R. Schober, “Optimal 3D-trajectory design and resource allocation for solar-powered UAV communication systems,” *IEEE Trans. Commun.*, vol. 67, no. 6, pp. 4281-4298, Jun. 2019.

[2] X. Yu, **D. Xu**, Y. Sun, D. W. K. Ng, and R. Schober, “Robust and secure wireless communications via intelligent reflecting surfaces,” *IEEE J. Sel. Areas Commun., Special Issue on Wireless Networks Empowered by Reconfigurable Intelligent Surfaces*, vol. 38, no. 11, pp. 2637-2652, Nov. 2020.

[3] X. Yu, **D. Xu**, D. W. K. Ng, and R. Schober, “IRS-assisted green communication systems: Provable convergence and robust optimization,” *IEEE Trans. Commun.*, vol. 69, no. 9, pp. 6313-6329, Sept. 2021.

[4] X. Yu, V. Jamali, **D. Xu**, D. W. K. Ng, and R. Schober, “Smart and reconfigurable wireless communications: From IRS modeling to algorithm design,” *IEEE Wirel. Commun.*, vol. 2, no. 6, pp. 118-125, Dec. 2021.

[5] Z. Ding, **D. Xu**, R. Schober, and H. V. Poor, “Hybrid NOMA offloading in multi-user MEC networks,” *IEEE Trans. Wireless Commun.*, vol. 21, no. 7, pp. 5377-5391, Jul. 2022.

Conference Publications:

[1] Y. Sun, D. W. K. Ng, **D. Xu**, L. Dai, and R. Schober, “Resource allocation for solar powered UAV communication systems,” in *Proc. IEEE Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Kalamata, Greece, Jun. 2018, pp. 1-5.

[2] X. Yu, **D. Xu**, and R. Schober, “MISO wireless communication systems via intelligent reflecting surfaces,” in *Proc. IEEE/CIC Int. Conf. Commun. China (ICCC)*, Changchun, China, Aug. 2019, pp. 735-740.

[3] X. Yu, **D. Xu**, and R. Schober, “Enabling secure wireless communications via intelligent reflecting surfaces,” in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Waikoloa, HI, USA, Dec. 2019, pp. 1-6.

[4] X. Yu, **D. Xu**, and R. Schober, “Optimal beamforming for MISO communications via intelligent reflecting surfaces,” in *Proc. IEEE Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Atlanta, GA, USA, May 2020, pp. 1-5.

[5] X. Yu, **D. Xu**, D. W. K. Ng, and R. Schober, “Power-efficient resource allocation for multiuser MISO systems via intelligent reflecting surfaces,” in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Taiwan, Dec. 2020, pp. 1-6.

Thanks for your attention.
Any question?

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[1] `https://www.lemondeinformatique.fr/actualites/lire-huawei-et-lg-u-testent-la-5g-avec-un-drone-relais-70106.html`

[2] `https://www.softbank.jp/sbnews/entry/20200914_01`

[3] J. -B. Gros et al., “A Reconfigurable Intelligent Surface at mmWave Based on a Binary Phase Tunable Metasurface,” *IEEE Open J. Commun. Soc.*, vol. 2, no.8, May 2021, pp. 1055-1064.

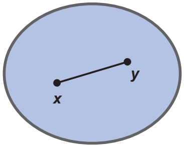
[4] L. Dai et al., “Reconfigurable Intelligent Surface-Based Wireless Communications: Antenna Design, Prototyping, and Experimental Results,” *IEEE Access*, vol. 8, Mar. 2020, pp. 45913-45923.

Convex Optimization Problems

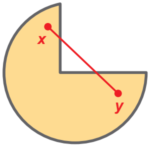
Definition (Convex Function)

A function $f : \mathbb{X} \rightarrow \mathbb{R}$ *is convex if its domain* $\mathbb{X}$ *is a convex set and for any* $x, y \in \mathbb{X}$ *and* $0 \leq \alpha \leq 1$*, we have*

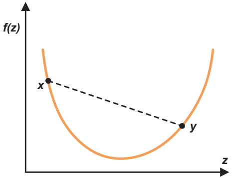
$$f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y).$$



Convex set



Non-convex set



Convex Optimization Problems

A convex optimization problem in standard form is given by

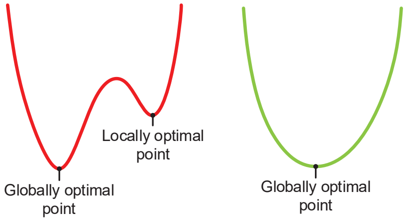
$$\begin{aligned} \underset{\mathbf{x}}{\text{minimize}} \quad & f(\mathbf{x}) \\ \text{s.t.} \quad & g_i(\mathbf{x}) \leq 0, \;\; i = 1, \cdots, m, \\ & h_i(\mathbf{x}) = 0, \;\; i = 1, \cdots, p. \end{aligned}$$

- $\mathbf{x} \in \mathbb{R}^n$: Variable to be optimized
- $f(\mathbf{x}): \; \mathbb{R}^n \longrightarrow \mathbb{R}$: Convex objective function
- $g_i(\mathbf{x}): \; \mathbb{R}^n \longrightarrow \mathbb{R}$, $i = 1, \cdots, m$: Convex inequality constraints
- $h_i(\mathbf{x}): \; \mathbb{R}^n \longrightarrow \mathbb{R}$, $i = 1, \cdots, p$: Affine equality constraints

Convex Optimization Problems

A convex optimization problem in standard form is given by

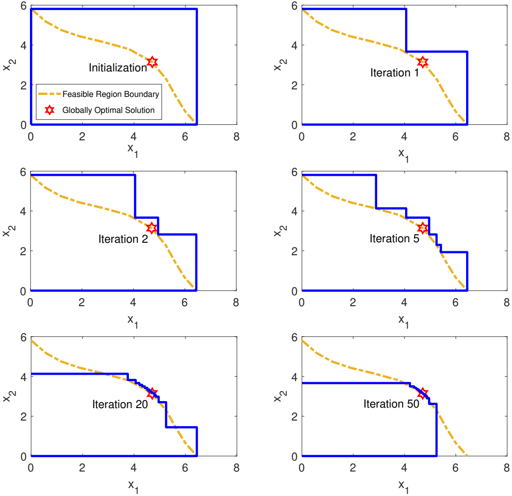
$$\begin{aligned} \underset{\mathbf{x}}{\text{minimize}} \quad & f(\mathbf{x}) \\ \text{s.t.} \quad & g_i(\mathbf{x}) \leq 0, \;\; i = 1, \cdots, m, \\ & h_i(\mathbf{x}) = 0, \;\; i = 1, \cdots, p. \end{aligned}$$



One fundamental property of convex optimization problems is that **any local optimum is also the global optimum**

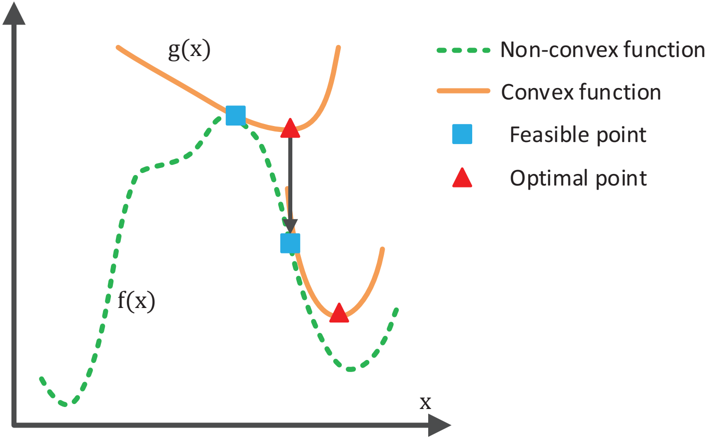
Monotonic Optimization

Exploit the monotonicity of the reformulated problem to finding **globally optimal solution**



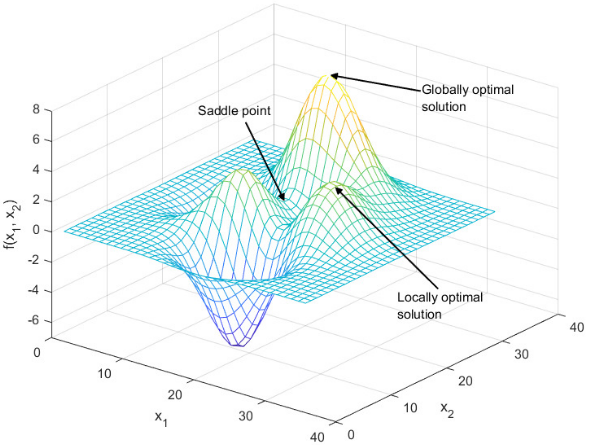
Successive Convex Approximation Method

Approximate a non-convex function by a convex function to finding **locally optimal solution** in a few iterations

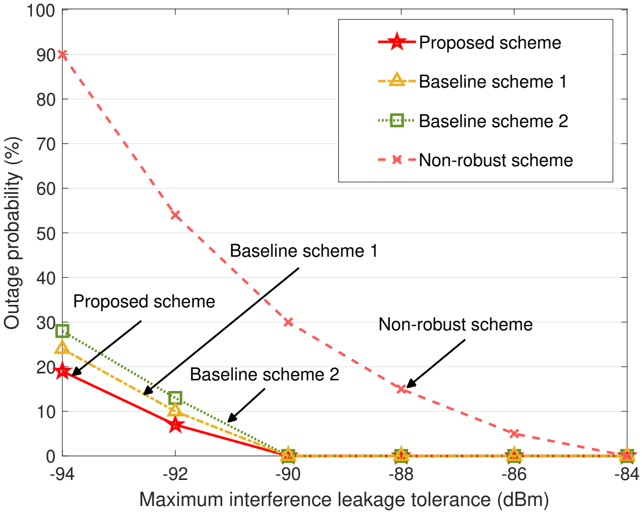


Block Coordinate Descent Method

BCD-based algorithm potentially converges to **global optimum**, **local optimum**, and **saddle point**



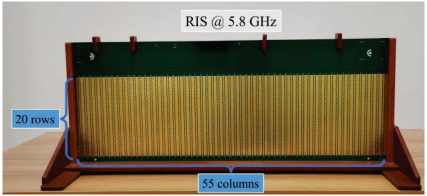
Simulation Results: Outage Probability versus Maximum Interference Leakage Tolerance



- 8 antennas, 8 IRS elements, 3 uplink users, 2 downlink users, 2 primary users, maximum DL transmit power $P_{\max}^{\mathrm{DL}} = 30$ dBm
- **Baseline scheme 1**: FD CR network does not employ IRS
- **Baseline scheme 2**: Secondary BS operates in the half-duplex mode
- **Non-robust scheme**: Treat the estimated channel state information (CSI) of the primary users as perfect CSI

IRS

- Practical IRSs comprise hundreds or thousands of elements



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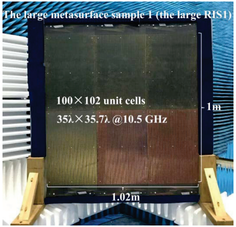

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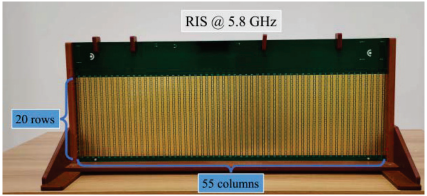
IRS

- Practical IRSs comprise hundreds or thousands of elements



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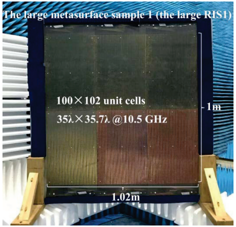

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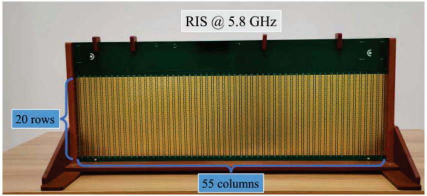
Element-wise optimization are not feasible for real-time online design of practical IRS

IRS

- Practical IRSs comprise hundreds or thousands of elements



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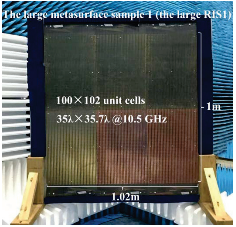

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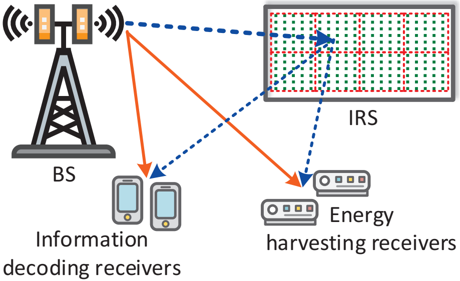
Contribution 3

Develop scalable algorithm to facilitate real-time design for large IRS-assisted SWIPT systems

D. Xu, V. Jamali, X. Yu, D. W. K. Ng, and R. Schober, “Optimal resource allocation design for large IRS-assisted SWIPT systems: A scalable optimization framework,” *IEEE Trans. Commun.*, vol. 70, no. 2, pp. 1423-1441, Feb. 2022.

Scalable Optimization Framework for Large IRS-Assisted SWIPT Systems

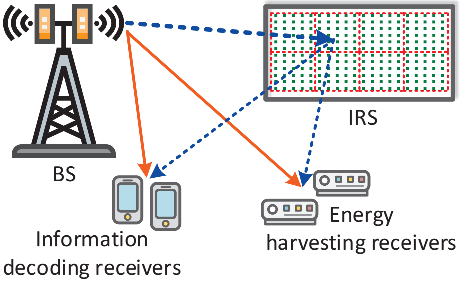
A BS serves a set of information decoding receivers and energy harvesting receivers with the help of a large IRS



Scalable Optimization Framework for Large IRS-Assisted SWIPT Systems

A BS serves a set of information decoding receivers and energy harvesting receivers with the help of a large IRS

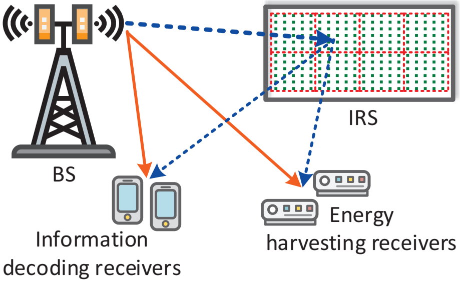
- Divide large IRS into several tiles



Scalable Optimization Framework for Large IRS-Assisted SWIPT Systems

A BS serves a set of information decoding receivers and energy harvesting receivers with the help of a large IRS

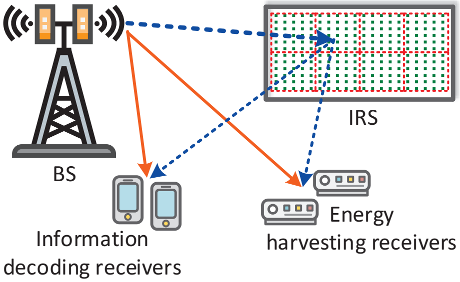
- Divide large IRS into several tiles
- Offline design elements in each tile to support a set of transmission modes



Scalable Optimization Framework for Large IRS-Assisted SWIPT Systems

A BS serves a set of information decoding receivers and energy harvesting receivers with the help of a large IRS

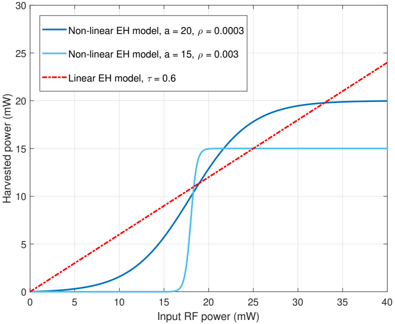
- Divide large IRS into several tiles
- Offline design elements in each tile to support a set of transmission modes
- Online select the best transmission mode for each tile



Scalable Optimization Framework for Large IRS-Assisted SWIPT Systems

A BS serves a set of information decoding receivers and energy harvesting receivers with the help of a large IRS

- Divide large IRS into several tiles
- Offline design elements in each tile to support a set of transmission modes
- Online select the best transmission mode for each tile
- Practical non-linear energy harvesting model



Transmission Mode Pre-Selection for Online Optimization

- The number of scatterers is limited and the locations of the scatterers are fixed, only a limited number of AoAs and AoDs can be used for transmission
- **Not all** the elements in the offline transmission mode set will contribute to system performance enhancement

  ⟹ Refine transmission mode set to facilitate efficient online optimization
- Develop two new refining criteria respectively taking into account **user fairness** and exploiting **concrete features of SWIPT systems**

Optimization Problem Formulation

For a given refined transmission mode set

Minimization of BS total transmit power

$$\begin{aligned} \underset{\substack{\mathbf{V}\succeq\mathbf{0},\mathbf{V}\in\mathbb{H}^{N_\mathrm{T}},\\ \mathbf{w}_k, b_{s,t}}}{\text{minimize}} \quad & \sum_{k\in\mathcal{K}} \|\mathbf{w}_k\|^2 + \mathrm{Tr}(\mathbf{V}) \quad \text{(BS transmit power)} \\ \text{s.t.} \quad & \text{C1: } \Gamma_k(\mathbf{V},\mathbf{w}_k,b_{s,t}) \geq \Gamma_{\mathrm{req}_k}, \ \forall k, \quad \text{(quality-of-service constraint)} \\ & \text{C2: } \Upsilon_j^{\mathrm{EH}}(\mathbf{V},\mathbf{w}_k,b_{s,t}) \geq E_{\mathrm{req}_j}, \ \forall j, \quad \text{(energy harvesting constraint)} \\ & \text{C3: } b_{s,t} \in \{0,1\}, \ \forall s \in \mathcal{S}_\mathrm{R}, \ \forall t \in \widehat{\mathcal{T}}, \quad \text{(mode selection constraint)} \\ & \text{C4: } \sum_{s\in\mathcal{S}_\mathrm{R}} b_{s,t} = 1, \ \forall t \in \widehat{\mathcal{T}}. \quad \text{(mode selection constraint)} \end{aligned}$$

Optimization Problem Formulation

For a given refined transmission mode set

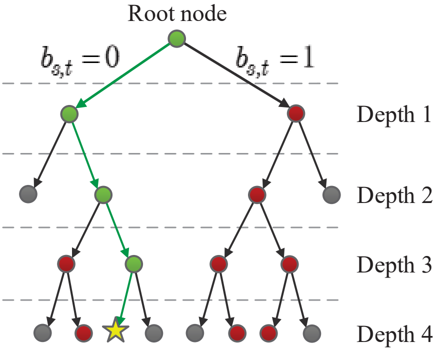
Minimization of BS total transmit power

$$
\begin{array}{rl}
\underset{\substack{\mathbf{V}\in\mathbb{H}^{N_{\mathrm{T}}},\mathbf{V}\succeq\mathbf{0},\\ \mathbf{w}_k,b_{s,t}}}{\text{minimize}} & \displaystyle\sum_{k\in\mathcal{K}} \|\mathbf{w}_k\|^2 + \mathrm{Tr}(\mathbf{V}) \\
\text{s.t.} & \text{C1: } \Gamma_k(\mathbf{V},\mathbf{w}_k,b_{s,t}) \geq \Gamma_{\mathrm{req}_k},\ \forall k, \quad \text{(non-convex constraint)} \\
 & \text{C2: } \Upsilon_j^{\mathrm{EH}}(\mathbf{V},\mathbf{w}_k,b_{s,t}) \geq E_{\mathrm{req}_j},\ \forall j, \quad \text{(non-convex constraint)} \\
 & \text{C3: } b_{s,t}\in\{0,1\},\ \forall s\in\mathcal{S}_{\mathrm{R}},\ \forall t\in\widehat{\mathcal{T}}, \quad \text{(binary constraint)} \\
 & \text{C4: } \displaystyle\sum_{s\in\mathcal{S}_{\mathrm{R}}} b_{s,t} = 1,\ \forall t\in\widehat{\mathcal{T}}.
\end{array}
$$

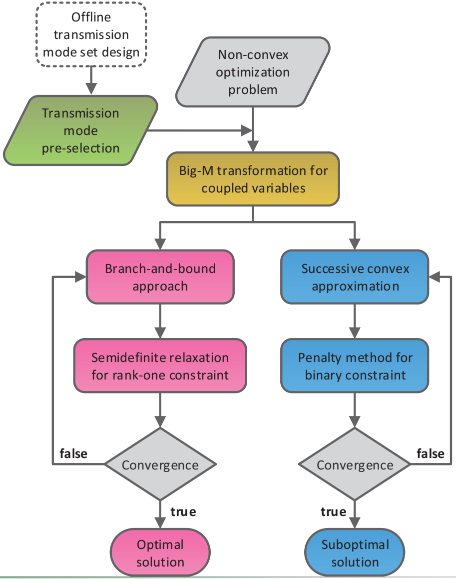
A non-convex combinatorial problem;
nevertheless, the **optimal** algorithm is developed

Branch-and-Bound-Based Optimal Scheme

- Exploit **tree traversal** and progressively partition the feasible set until finding the **globally optimal** solution
- Develop **bound construction criterion**, **partition rule**, and **branching strategy**



Flow Chart of the Developed Scheme



Offline transmission mode set design

Non-convex optimization problem

Transmission mode pre-selection

Big-M transformation for coupled variables

Branch-and-bound approach

Successive convex approximation

Semidefinite relaxation for rank-one constraint

Penalty method for binary constraint

Convergence

false

true

Convergence

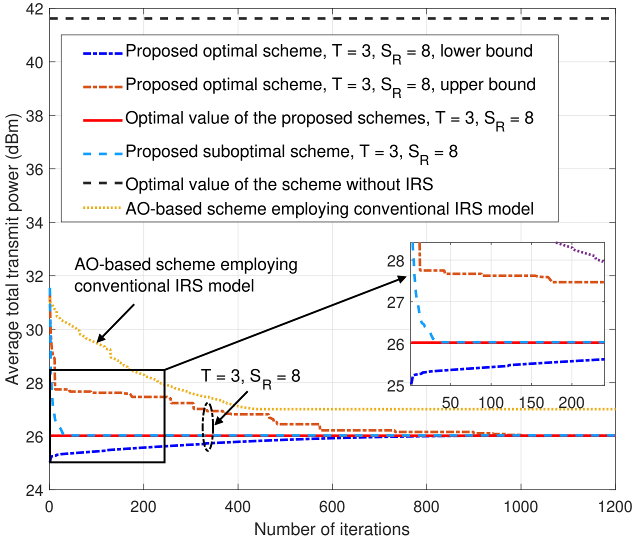
false

true

Optimal solution

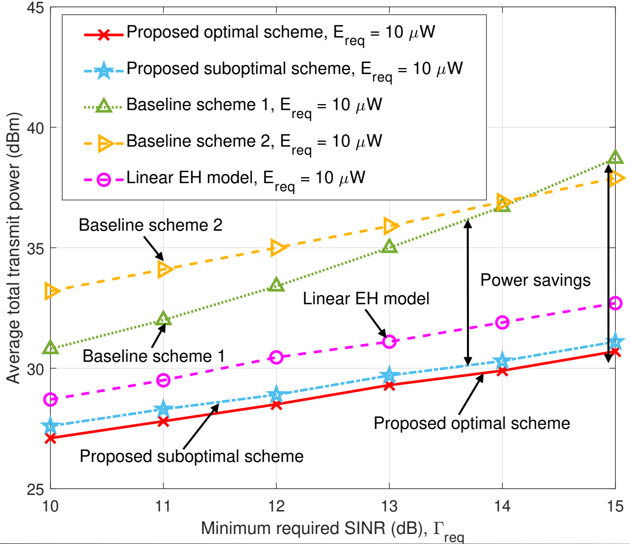
Suboptimal solution

Simulation Results: Convergence Behaviors of the Developed Algorithms



- 10 antennas, 600 IRS elements, 2 information decoding receivers, and 2 energy harvesting receivers
- **AO-based scheme employing conventional IRS model**: Employ element-wise IRS optimization framework and alternatingly optimize IRS phase shift matrix and BS beamforming vectors

Simulation Results: Average Total Transmit Power



- 8 antennas, 3 tiles, 8 transmission modes, 2 information decoding receivers, and 2 energy harvesting receivers
- **Baseline scheme 1**: Randomly chosen transmission mode for each tile + isotropic radiation pattern for covariance matrix of energy signal
- **Baseline scheme 2**: Randomly generated IRS phase shift matrix
- **Linear EH model**: Adopt a linear model for energy harvesting receivers

References

[5] X. Pei et al., “RIS-aided wireless communications: Prototyping, adaptive beamforming, and indoor/outdoor field trials,” *IEEE Trans. Commun.* vol.69, no.12, Dec. 2021, pp.8627-8640.

[6] W. Tang et al., “Wireless Communications With Reconfigurable Intelligent Surface: Path Loss Modeling and Experimental Measurement,” in *IEEE Trans. Wireless Commun.*, vol. 20, no. 1, Jan. 2021, pp. 421-439.