Cell-Free MIMO-Assisted ISAC: Joint AP Switching and Power Allocation

Bin Yan[1], Zheng Wang[1], Amin Sakzad[2], Yongming Huang[1], and Michail Matthaiou[3]

[1]*Southeast University, Nanjing, China*

[2]*Monash University, Melbourne, Australia*

[3]*Queen's University, Belfast, U.K.*

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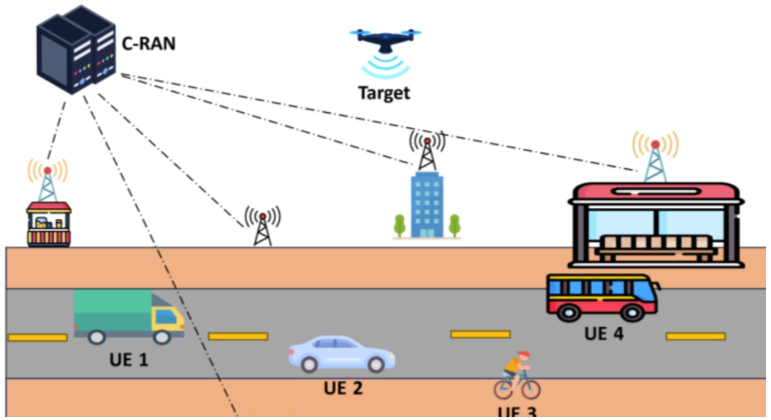
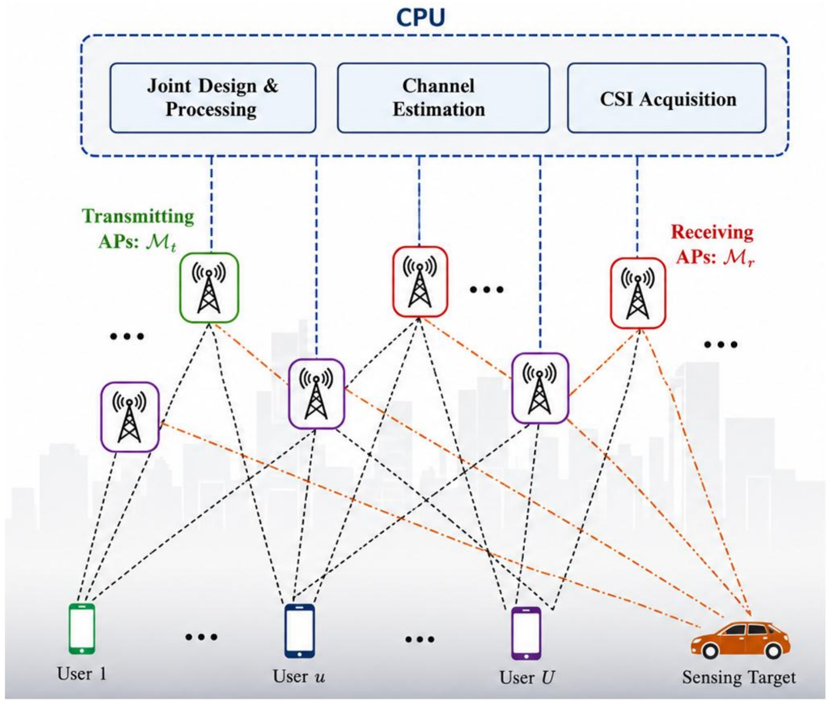
1 Background

Limitations of centralized mMIMO-ISAC

With the evolution toward **B5G and 6G** wireless communication systems:

- Co-located antennas may cause uneven coverage.
- Inter-cell interference degrades both communication and sensing.





Challenges towards MIMO evolution

- **Distributed APs provide better spatial diversity.**
- **AP switching enables more flexible interference management.**

2 Problem & Challenge

Dynamic AP mode switching

Communication AP (C-AP)

- Serve downlink users.
- Use partial zero-forcing precoding.
- Strong users: FZF precoding.
- Weak users: MRT precoding.

$$\mathbf{x}_m^c = \sum_{k\in\mathcal{S}_m} \sqrt{\rho_d \eta_{mk}^c}\,\mathbf{t}_{mk}^F x_k^c + \sum_{k\in\mathcal{W}_m} \sqrt{\rho_d \eta_{mk}^c}\,\mathbf{t}_{mk}^M x_k^c.$$

Sensing AP (S-AP)

- Transmit probing signals.
- Illuminate multiple sensing zones.
- Use steering-vector-based beams.

$$\mathbf{x}_m^s = \sum_{l\in\mathcal{L}} \sqrt{\rho_d \eta_{ml}^s}\,\mathbf{a}_N(\theta_{ml}) x_{ml}^s$$

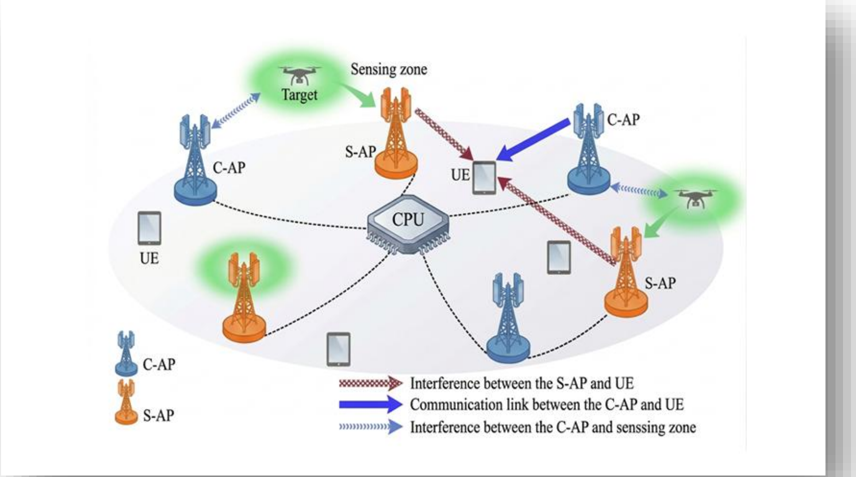


Fig. 1. Considered CF-mMIMO-assisted ISAC system.

Overall transmitted signal: $\mathbf{x}_m = a_m \mathbf{x}_m^c + (1 - a_m)\mathbf{x}_m^s$

Dynamic AP switching separates communication and sensing functions, reducing mutual interference and improving resource flexibility.

2 Problem & Challenge

Communication: spectral efficiency (SE)

Use-and then-forget principle:

$$\mathrm{SINR}_k\left(\boldsymbol{\Theta}^c, \boldsymbol{\Theta}^s\right) = \frac{\rho_d\left(\sum_{m\in\mathcal{M}}\sqrt{\eta^c_{mk}}\gamma_{mk}\varrho_{mk}\right)^2}{1+\rho_d N\sum_{m\in\mathcal{M}}\sum_{l\in\mathcal{L}}\eta^s_{ml}\beta_{mk}+\rho_d\sum_{m\in\mathcal{M}}\sum_{k'\in\mathcal{K}}\left(\eta^c_{mk'}\gamma_{mk'}\varpi_{mk}\right.}$$

Shannon's theorem:

$$\mathrm{SE}_k(\boldsymbol{\Theta}^c, \boldsymbol{\Theta}^s) = \left(1-\frac{\tau_u}{\tau}\right)\log_2\left(1+\mathrm{SINR}_k\left(\boldsymbol{\Theta}^c, \boldsymbol{\Theta}^s\right)\right)$$

- Dependent variable: C-AP and S-AP power allocation coefficient
- Other users' data + sensing signals act as effective noise.

Sensing: mainlobe-to-average-sidelobe ratio(MASR)

Minimize the sensing beampattern gain:

$$\mathrm{MASR}_l \triangleq \frac{P^{\mathrm{ave}}_{\mathrm{Sen,DS}}(\theta_{t,ml})}{P^{\mathrm{ave}}_{\mathrm{Com}}(\theta_{t,m})+P^{\mathrm{ave}}_{\mathrm{SenDST}}(\theta_{t,ml})}.$$

$$\mathrm{MASR}_l\left(\boldsymbol{\Theta}^c, \boldsymbol{\Theta}^s\right) = \frac{\sum_{m\in\mathcal{M}}N^2\eta^s_{ml}}{\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}}\eta^c_{mk}\gamma_{mk}\nu_{mk}+\sum_{m\in\mathcal{M}}\sum_{l'\in\mathcal{L}\setminus l}\eta^s_{ml'}|\mathbf{a}^{\dagger}_N(\theta_{ml})\mathbf{a}_N(\theta_{ml'})|^2}$$

- Average sensing power pattern distortion as well as communication distortion
- Users' data + other sensing zones sensing signals act as effective noise.

2 Problem & Challenge

Problem Formulation

$$\mathcal{P}_1: \max_{\mathbf{a},\boldsymbol{\Theta}^c,\boldsymbol{\Theta}^s} \min_{k\in\mathcal{K}} \mathrm{SE}_k(\boldsymbol{\Theta}^c,\boldsymbol{\Theta}^s)$$

$$\text{s.t.} \quad \mathrm{MASR}_l(\boldsymbol{\Theta}^c,\boldsymbol{\Theta}^s) \geq \kappa, \forall l \in \mathcal{L},$$

$$\sum_{k\in\mathcal{K}} \eta_{mk}^c \gamma_{mk} \nu_{mk} \leq a_m, \forall m \in \mathcal{M},$$

$$\sum_{l\in\mathcal{L}} \eta_{ml}^s \leq \frac{(1-a_m)}{N}, \forall m \in \mathcal{M},$$

Power constraints

$$a_m \in \{0,1\}, \forall m \in \mathcal{M}$$

Description

Objective: Uniform QoS

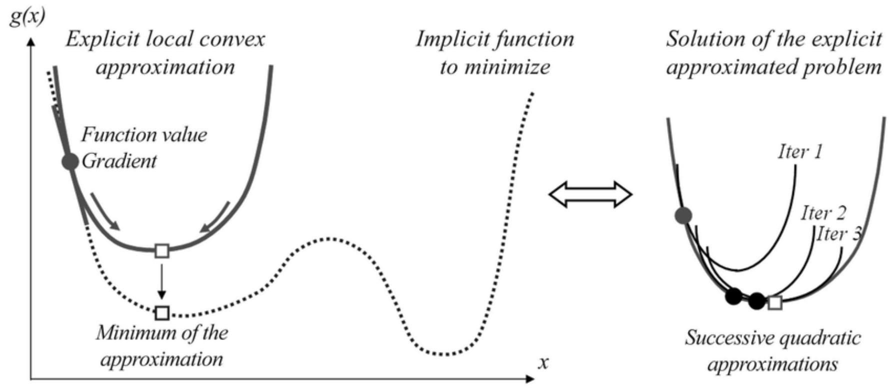
s.t.: Achieve the desired MASR level

Mixed integer Non-convex Optimization Problem !

Challenge

- ***Variable properties***: Mixed integer problem, there are both integer variables and continuous variables.
- ***Variable coupling:*** There is a coupling property between integer variables and discrete variables.
- ***Concavity:*** Objective function and constrained height nonconvex.

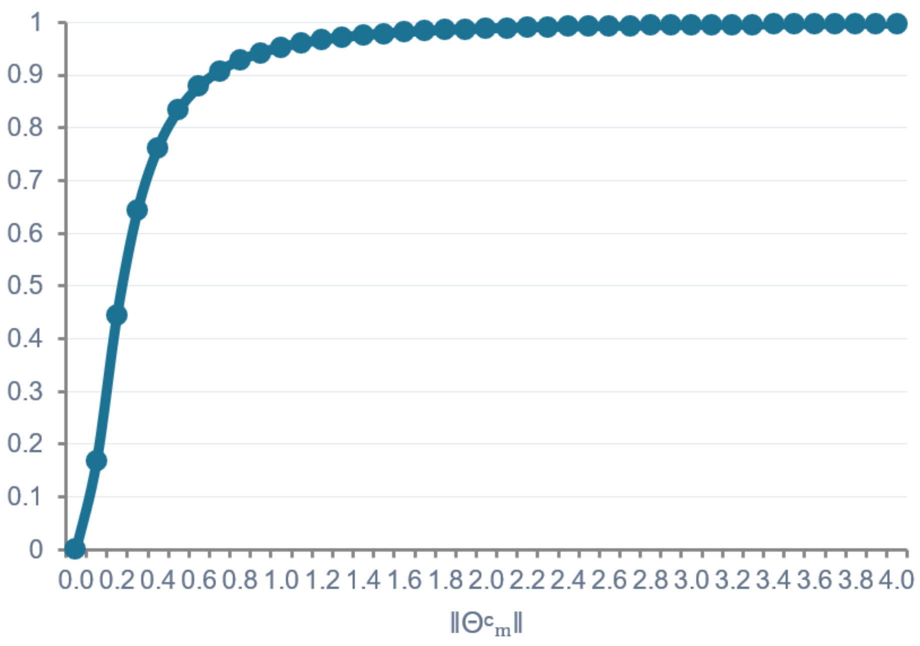
Traditional solutions



- Variable relaxation: $\{0,1\} \rightarrow [0,1]$
- Successive convex approximation (SCA) for Nonconvex Optimization

Unaffordable computational complexity!

KEY: use the coupling between discrete variables and continuous variables



P1 → P2: binary a_m removed; constraint becomes $N \sum_l \eta^s_{ml} \leq 1 - \sigma(\Theta^c_m)$

$\|\boldsymbol{\Theta}^c_m\| = 0,$ AP operates in sensing mode ($a_m = 0$)

$\|\boldsymbol{\Theta}^c_m\| > 0 \Longleftrightarrow a_m = 1,$

forming a step-function mapping (non-smooth).

$$\sigma\left(\boldsymbol{\Theta}^c_m\right) = \frac{\|\boldsymbol{\Theta}^c_m\|^2}{\|\boldsymbol{\Theta}^c_m\|^2 + \delta}, \quad \boldsymbol{\Theta}^c_m \in \mathbb{R}^{1\times K}_+,$$

Approximate characterization of discrete variables by continuous variables

Original problem

$$
\begin{aligned}
\mathcal{P}_1: \max_{\mathbf{a},\boldsymbol{\Theta}^c,\boldsymbol{\Theta}^s} \min_{k\in\mathcal{K}} \quad & \mathrm{SE}_k(\boldsymbol{\Theta}^c,\boldsymbol{\Theta}^s) \\
\text{s.t.} \quad & \mathrm{MASR}_l(\boldsymbol{\Theta}^c,\boldsymbol{\Theta}^s) \geq \kappa, \forall l \in \mathcal{L}, \\
& \sum_{k\in\mathcal{K}} \eta^c_{mk}\gamma_{mk}\nu_{mk} \leq a_m, \forall m \in \mathcal{M}, \\
& \sum_{l\in\mathcal{L}} \eta^s_{ml} \leq \frac{(1-a_m)}{N}, \forall m \in \mathcal{M}, \\
& a_m \in \{0,1\}, \forall m \in \mathcal{M},
\end{aligned}
$$

Problems after smooth representation

$$
\begin{aligned}
\mathcal{P}_2: \max_{\boldsymbol{\Theta}} f(\boldsymbol{\Theta}) \triangleq \min_{k\in\mathcal{K}} \quad & \mathrm{SINR}_k(\boldsymbol{\Theta}) \\
\text{s.t.} \quad & \mathrm{MASR}_l(\boldsymbol{\Theta}) \geq \kappa, \forall l \in \mathcal{L}, \\
& \sum_{k\in\mathcal{K}} \eta^c_{mk}\gamma_{mk}\nu_{mk} \leq 1, \forall m \in \mathcal{M}, \\
& N\sum_{l\in\mathcal{L}} \eta^s_{ml} \leq 1 - \frac{\|\boldsymbol{\Theta}^c_m\|^2}{\|\boldsymbol{\Theta}^c_m\|^2+\delta}, \forall m \in \mathcal{M}.
\end{aligned}
$$

- Mixed integer and continuous
- Non-convex problem

→

- ***Only continuous !***
- Non-convex problem
- Non-smooth objective function

Smoothing of the objective function

$$f(\boldsymbol{\Theta}) = \min_{k\in\mathcal{K}} \ \mathrm{SINR}_k\left(\boldsymbol{\Theta}\right) \approx -f_{\chi}(\boldsymbol{\Theta})$$
$$\triangleq -\frac{1}{\chi}\log\left(\frac{1}{K}\sum_{k\in\mathcal{K}}\exp\left(-\chi\mathrm{SINR}_k\left(\boldsymbol{\Theta}\right)\right)\right),$$

$\chi > 0$ is the smoothness parameter.

$$f(\boldsymbol{\Theta}) + \frac{\ln K}{\chi} \geq -f_{\chi}(\boldsymbol{\Theta}) \geq f(\boldsymbol{\Theta}).$$

- ***The objective function changes from non-smooth to smooth***: making the gradient algorithm applicable
- ***Select appropriate smoothness parameter***: prevent numerical spillover while ensuring high approximation

Take penalties to deal with constraints

$$Q_1(\boldsymbol{\Theta}) \triangleq \sum_{l\in\mathcal{L}} \left[\max\left(0, \kappa - \mathrm{MASR}_l\left(\boldsymbol{\Theta}\right)\right)\right]^2,$$

$$Q_2(\boldsymbol{\Theta}) \triangleq \sum_{m\in\mathcal{M}} \left[\max\left(0, N\sum_{l\in\mathcal{L}} \eta_{ml}^s + \frac{\|\boldsymbol{\Theta}_m^c\|^2}{\|\boldsymbol{\Theta}_m^c\|^2+\delta} - 1\right)\right]^2.$$

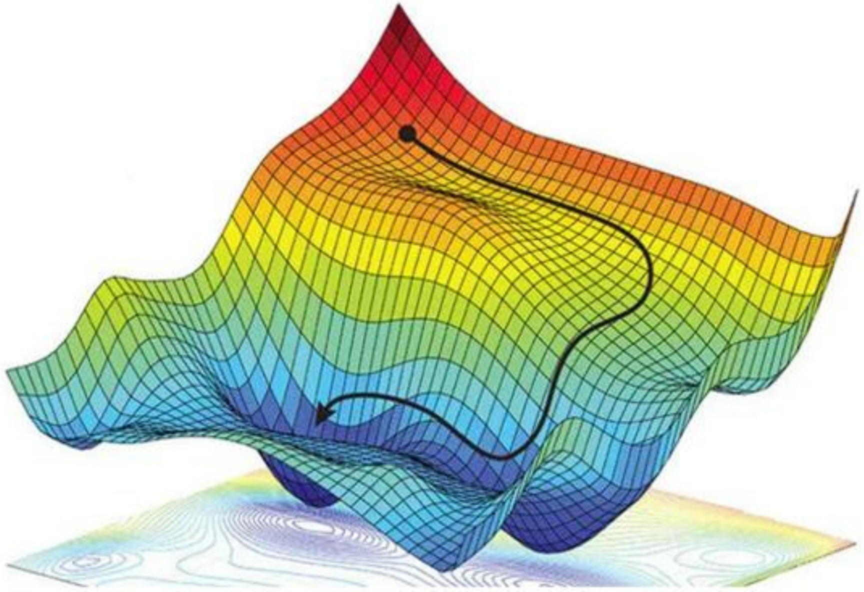
Final objective function

$$H_{\chi,\boldsymbol{\lambda}}(\boldsymbol{\Theta}) \triangleq f_\chi(\boldsymbol{\Theta}) + \sum_{i=1}^{2} \lambda_i \mu_i Q_i(\boldsymbol{\Theta}).$$

Non-convex smooth + convex non-smooth

$$\mathcal{P}_3: \quad \min_{\boldsymbol{\Theta}} \quad H_{\chi,\boldsymbol{\lambda}}(\boldsymbol{\Theta}) + I(\boldsymbol{\Theta}^c).$$

The proximal gradient method is suitable!



Core renewal formula of near end gradient method

$$\boldsymbol{\Theta}^{(t)} = \mathrm{prox}_{\alpha^{(t)},I}\left(\mathbf{Z}^{(t)} - \alpha^{(t)}\nabla H_{\chi,\boldsymbol{\lambda}}(\mathbf{Z}^{(t)})\right),$$

Smooth term: standard gradient descent

$$\mathrm{prox}_{\mathcal{C}}(\mathbf{X}) = \arg\min_{\boldsymbol{\Theta}\in\mathcal{C}} \|\boldsymbol{\Theta} - \mathbf{X}\|^2,$$

Non-smooth term: using convexity to simplify to nearest distance optimization problem

$$\mathrm{prox}_{\mathcal{C}}(\mathbf{X}) = \mathrm{prox}_{\mathcal{C}}(\tilde{\mathbf{X}}) = \arg\min_{\boldsymbol{\Theta}^c\in\mathcal{C}} \|\boldsymbol{\Theta}^c - \tilde{\mathbf{X}}\|^2$$

Projection further simplified: only related to communication AP power allocation coefficient

Lemma 1. *For given* $\tilde{\mathbf{X}}$, *the projection* $\text{prox}_{\mathcal{C}}(\tilde{\mathbf{X}})$ *for the communication PAC is given by the following analytical solution*

$$\eta_{mk}^{c,\star} = \max\left(0,\ \tilde{x}_{mk} - \frac{\xi_m}{2}\gamma_{mk}\nu_{mk}\right). \tag{24}$$

Here, $\tilde{x}_{mk}$ *is the* (m,k)*-th entry of* $\tilde{\mathbf{X}}$ *and* ξ_m *is the Lagrange multiplier determined according to the following condition*

$$\xi_m = \begin{cases} 0, & \text{if } \sum_{k\in\mathcal{K}} \max(0, \tilde{x}_{mk})\gamma_{mk}\nu_{mk} \le 1, \\ \text{the root of (29)}, & \text{otherwise}. \end{cases} \tag{25}$$

$$\sum_{k\in\mathcal{K}} \max\left(0,\ \tilde{x}_{mk} - \frac{\xi_m}{2}\gamma_{mk}\nu_{mk}\right)\gamma_{mk}\nu_{mk} = 1, \tag{29}$$

which is continuous and strictly decreasing in ξ_m. This solution essentially corresponds to a soft-thresholding operation, where the value of ξ_m can be efficiently obtained using bisection search or fixed-point iteration.

Algorithm 1: The **SC-JAPSPA** algorithm for $\mathcal{P}_3$

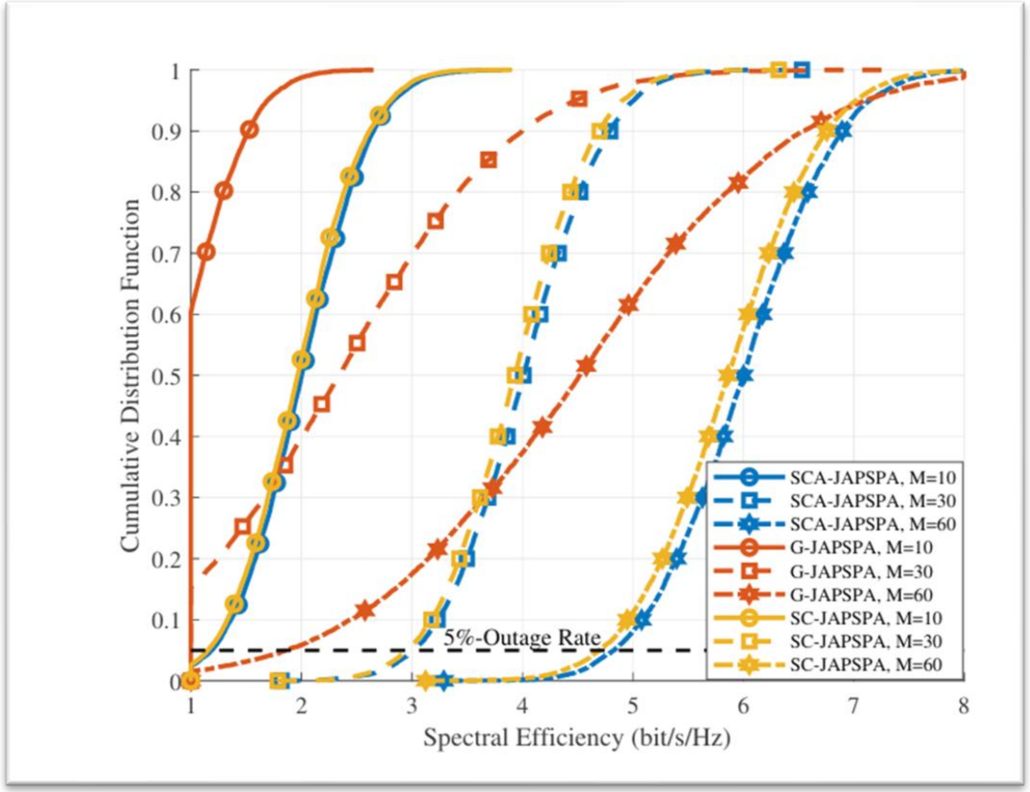
Input : $\mathbf{Z}^{(1)} = \mathbf{\Theta}^{(0)}, \mu_1 = 10^3, \mu_2 = 10, \beta = 2, \omega = 0.5, \boldsymbol{\lambda} = \mathbf{1}, t = 1, \varepsilon = 10^{-3}, \alpha^{(t)} = 10^{-3}$

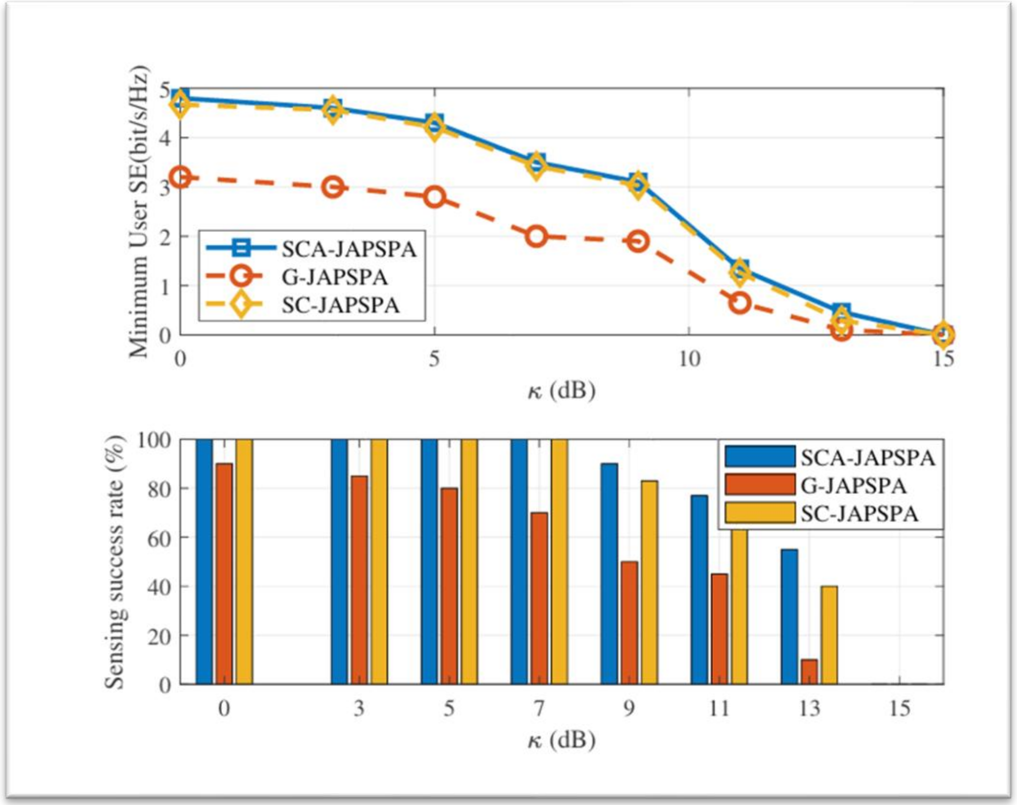
```
repeat                                                   // Penalty loop
    repeat                                               // APG-AM loop
        update Θ^(t) via (21) and v^(t) via (30)
        update Z^(t+1) and β via (31)
        if |H_{χ,λ}(Θ^(t)) − H_{χ,λ}(Θ^(t−1))| > ε then
            t = t + 1
        end
    until |H_{χ,λ}(Θ^(t)) − H_{χ,λ}(Θ^(t−1))| ≤ ε;
    increase the penalty coefficients λ_i = 10λ_i, i = 1, 2
until |Q_1(Θ^(t)) − Q_1(Θ^(t−1))| ≤ ε as well as
      |Q_2(Θ^(t)) − Q_2(Θ^(t−1))| ≤ ε;
```

Output: Stationary power allocation coefficients: $\mathbf{\Theta}^\star$

- Introducing auxiliary variables for ***momentum acceleration***
- ***Smooth Lipschitz***: monotonically converges to the stationary point

4 Numerical Results





- SC-JAPSPA provides near-SCA communication performance with better reliability than G-JAPSPA.
- SC-JAPSPA achieves a robust tradeoff between minimum user SE and sensing success rate.

TABLE I
COMPARISON BETWEEN THE EXECUTION TIME (IN SECONDS)

Algorithm	Number of APs (M)				Number of Users (K)				Number of Sensing Zones (L)			
	20	30	40	60	4	8	12	20	2	4	8	12
SCA-JAPSPA [1]	173.61	269.93	375.27	424.84	152.64	173.61	213.43	284.31	143.59	173.61	202.86	243.03
G-JAPSPA [1]	25.88	31.15	35.21	58.23	17.95	25.88	33.43	45.34	15.28	25.88	31.07	37.29
SC-JAPSPA (this work)	8.57	14.68	19.34	25.93	4.13	8.57	13.85	17.34	3.02	8.57	11.39	14.51

SC-JAPSPA: $\mathcal{O}(M \max{(K,L)}^2)$ $\ll$ SCA-JAPSPA: $\mathcal{O}(M^{3.5} \max{(K,L)}^{3.5})$

- SC-JAPSPA achieves near-benchmark performance with much lower runtime and complexity.

Thank You for Your Attention

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