Joint Probabilistic Shaping and Precoding Design for MU-MISO VLC Systems

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Contents

Introduction

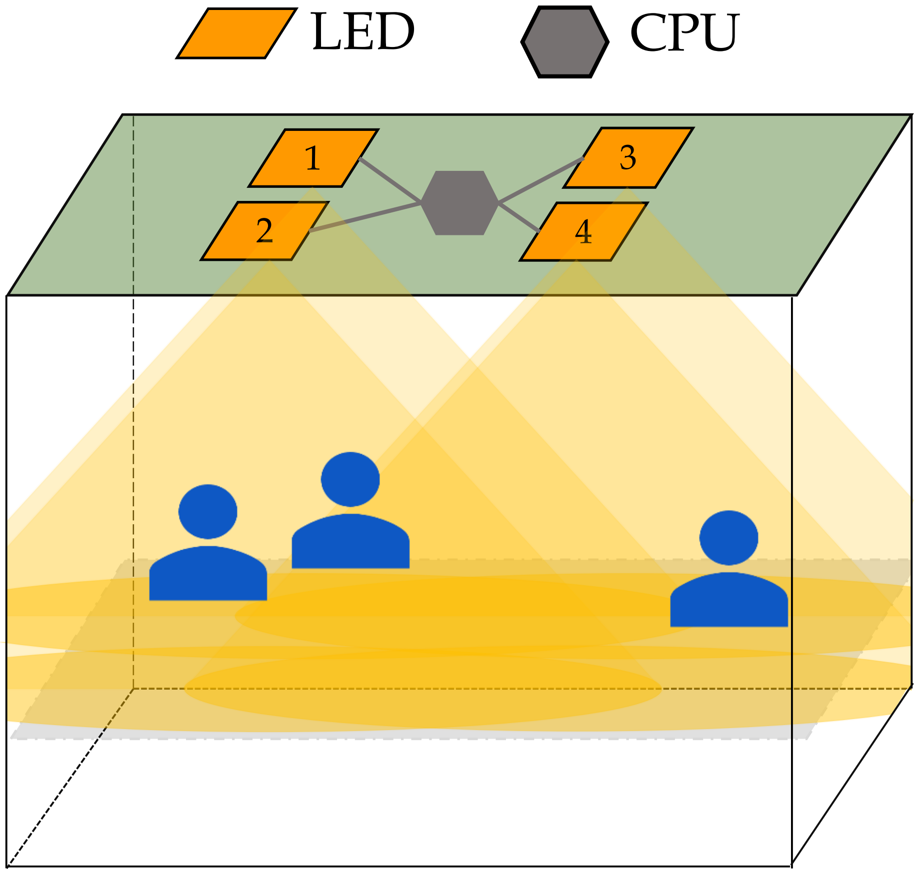
❑ Visible light communication (VLC)

- ❖ Dual functionality
  - Illumination (primary)
  - Communication (secondary)
- ❖ Immunity to interference from other electromagnetic sources
- ❖ Environment friendly
  - Hospital
  - Airplane

VLC network is expected to support multiple mobile users

Introduction

❑ Multi-user Multiple Input Single Output VLC system (MU-MISO VLC)



- N_T LEDs simultaneously serve K users
- Each user is equipped with a single-photodiode (PD) receiver

A multi-user multiple input single output (MU-MISO) VLC broadcast system

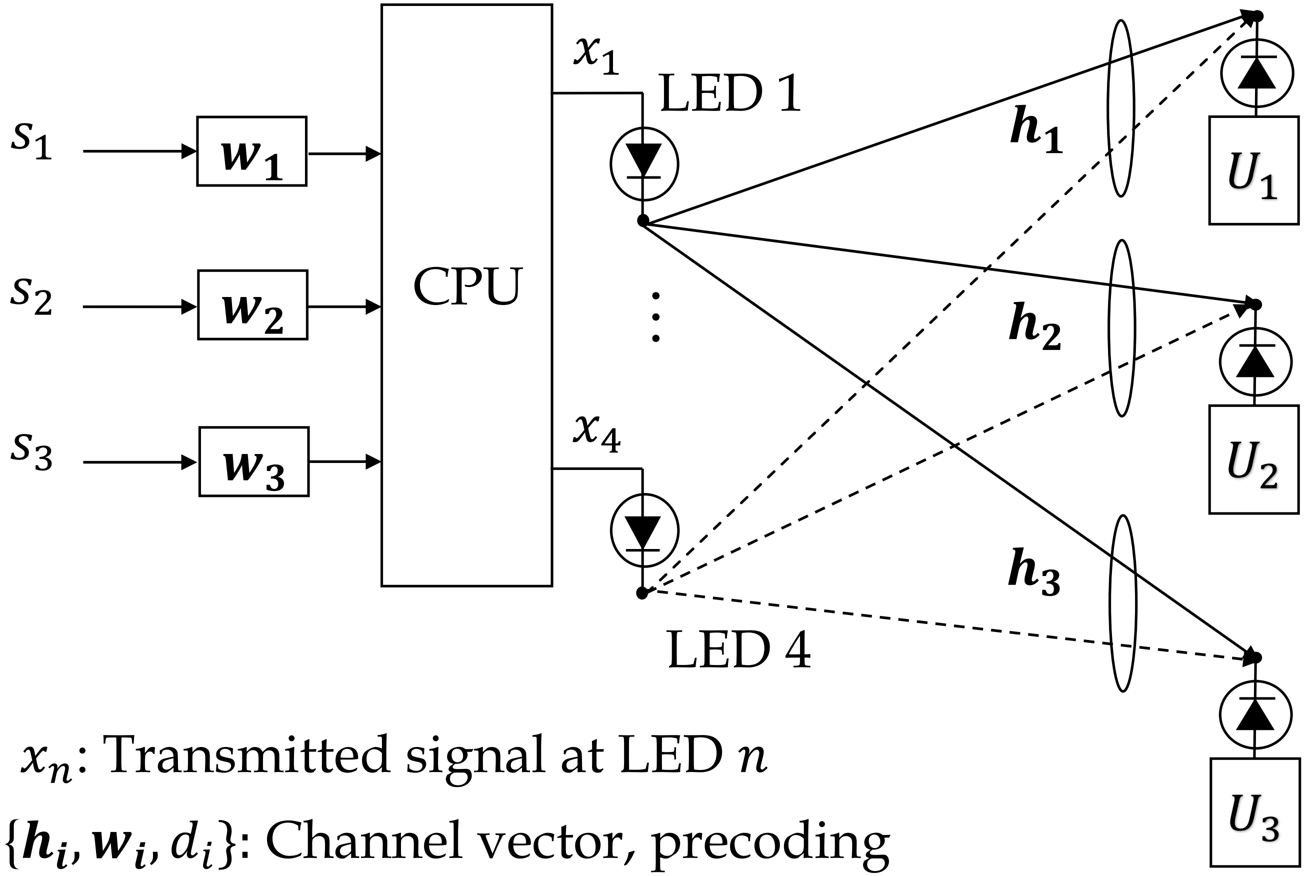
Drawbacks:

- Multi-user interference (MUI)
- Optical power constraint (peak and average)

Introduction

❑ Precoding design

Linearly encoding s_i by a vector $\boldsymbol{w_i}$ to reduce the effect of multi-user interference at received signal



x_n: Transmitted signal at LED n

$\{\boldsymbol{h_i}, \boldsymbol{w_i}, d_i\}$: Channel vector, precoding vector & data signal for i-th user

❑ Received signal at the i-th user

$$y_i = \boldsymbol{h_i w_i} s_i + \boldsymbol{h_i} \sum_{j=1, j\neq i}^{K} \boldsymbol{w_j} s_j + n_i$$

Multi-user interference (MUI)

❑ By generate precoding vector $\boldsymbol{w}$ based on the channel state information, MUI can be eliminated

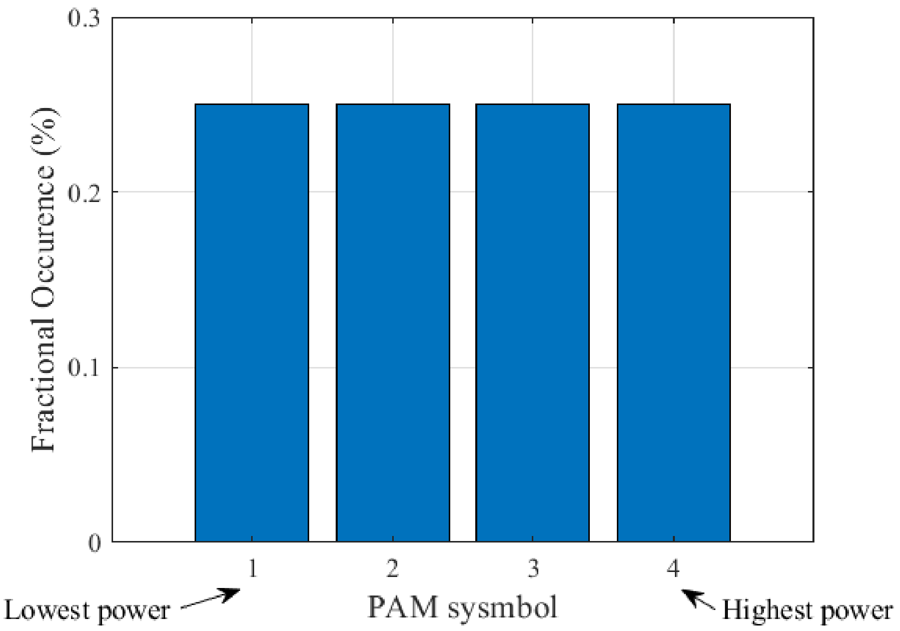
Introduction

PCS is an approach to enhance the sum rate under power constraints

❑ Probabilistic constellation shaping (PCS)

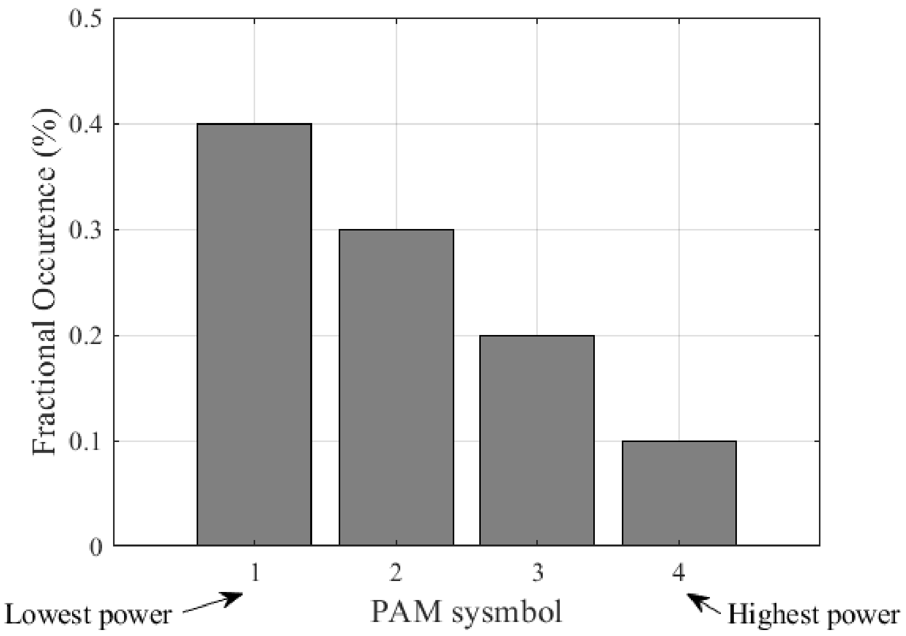
Standard transmission

- Each symbol transmitted with equal probability



Shaped transmission

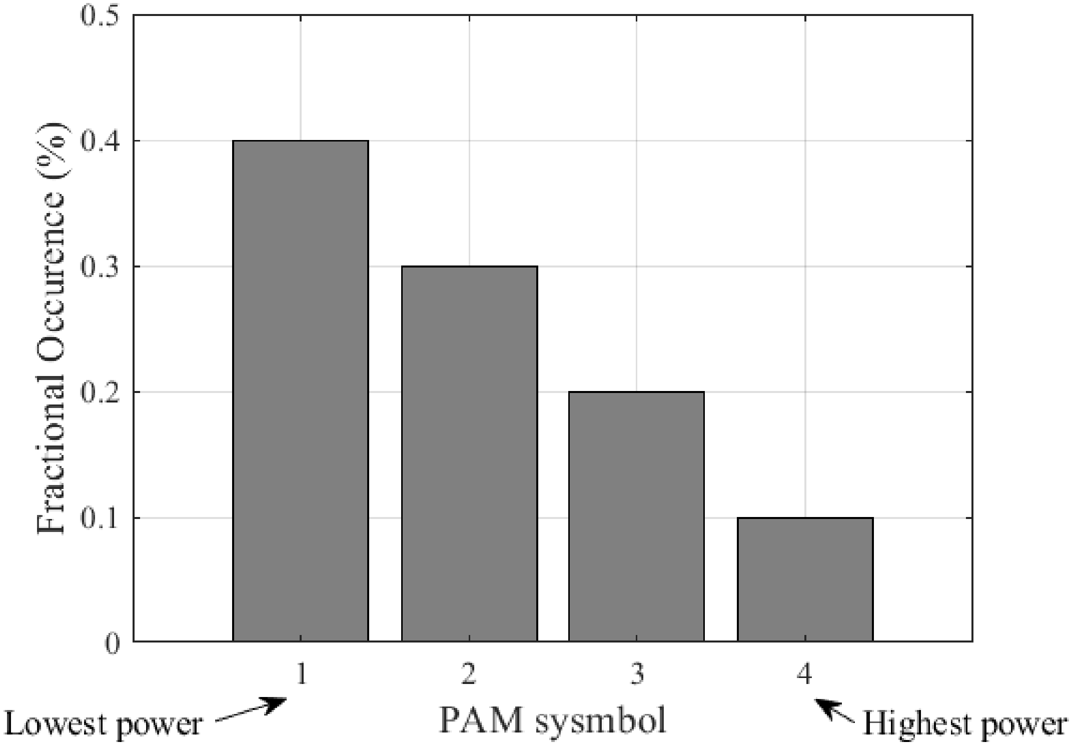
- Each symbol transmitted with different probability
- Higher power symbols transmitted less frequently



Introduction

❑ Probabilistic constellation shaping (PCS)

- Each symbol transmitted with different probability
- Higher power symbols transmitted less frequently



✓ Average power decreases

✓ Reduce non-linear effects in LEDs

➡ Improve the system’s sum rate under the power constraints

Introduction

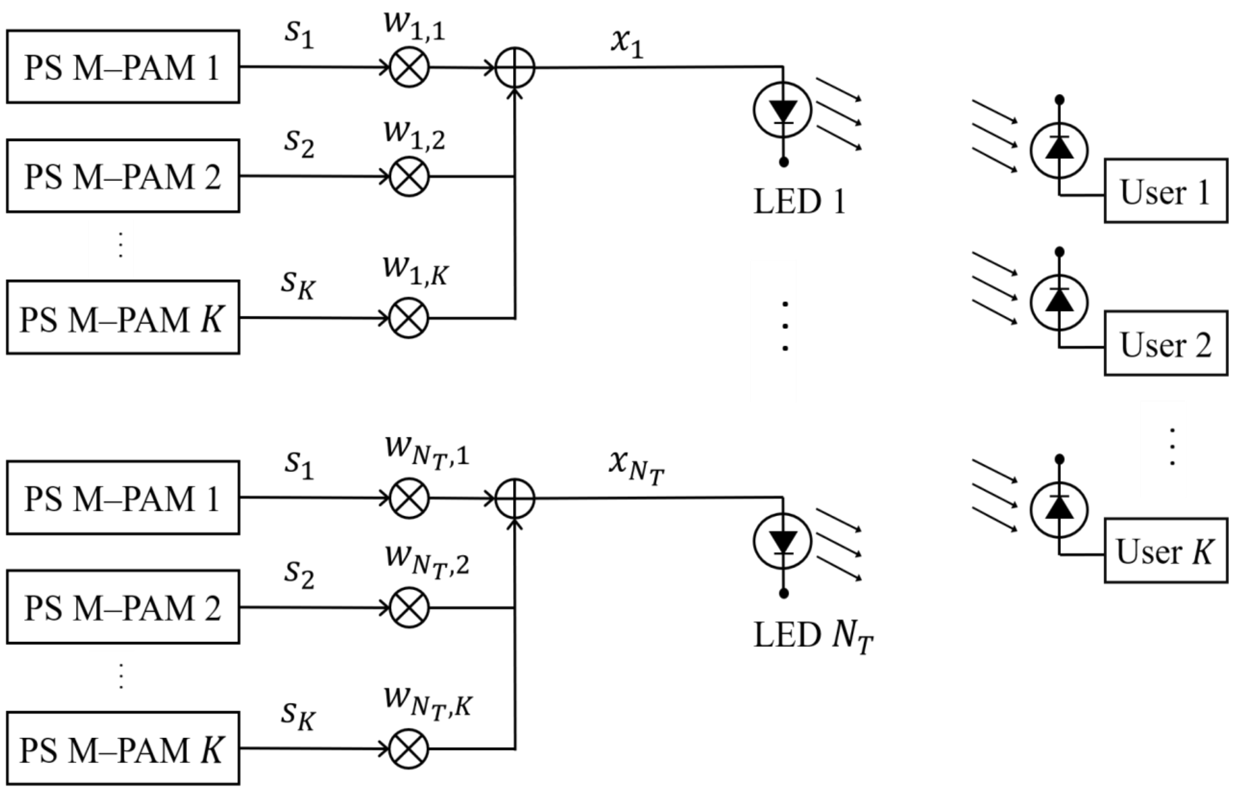
Reference	Main Contributions
[1] - 2022	Propose joint design of probabilistic M-PAM shaping and precoding to optimize the channel capacity of the MISO-VLC system with one user
[2] - 2022	Propose a novel adaptive coded spatial modulation scheme with probabilistic M-PAM shaping to improve the spectral efficiency of the MISO-VLC system with one user

➡ Our work is propose a joint design of precoding and probabilistic constellation shaping to enhance the sum-rate performance of the multi-user VLC system

[1] F. Yang and Y. Dong, "Joint Probabilistic Shaping and Beamforming Scheme for MISO VLC Systems," in IEEE Wireless Communications Letters, vol. 11, no. 3, pp. 508-512, March 2022, doi: 10.1109/LWC.2021.3134268.
[2] A. Kafizov, A. Elzanaty and M. -S. Alouini, "Probabilistic Shaping-Based Spatial Modulation for Spectral-Efficient VLC," in IEEE Transactions on Wireless Communications, vol. 21, no. 10, pp. 8259-8275, Oct. 2022, doi: 10.1109/TWC.2022.3164991.

System model

❑ MU-MISO VLC system with PCS



- $\boldsymbol{s} = [s_1 \quad s_2 \cdots \quad s_K]$: vector of data symbols for K users
- $s_k \sim \{s_{k,m_k}\}$: data symbol for user k, drawn from the PS M-PAM k

$$k \in \{1, 2, \dots, K\}, m_k \in \{1, 2, \dots, M\}$$

- $\boldsymbol{w}_k = [w_{k,1} \quad w_{k,2} \cdots \quad w_{k,N_T}]$ is the precoding vector for user k-th

System model

❑ Probabilistic shaping M-PAM k

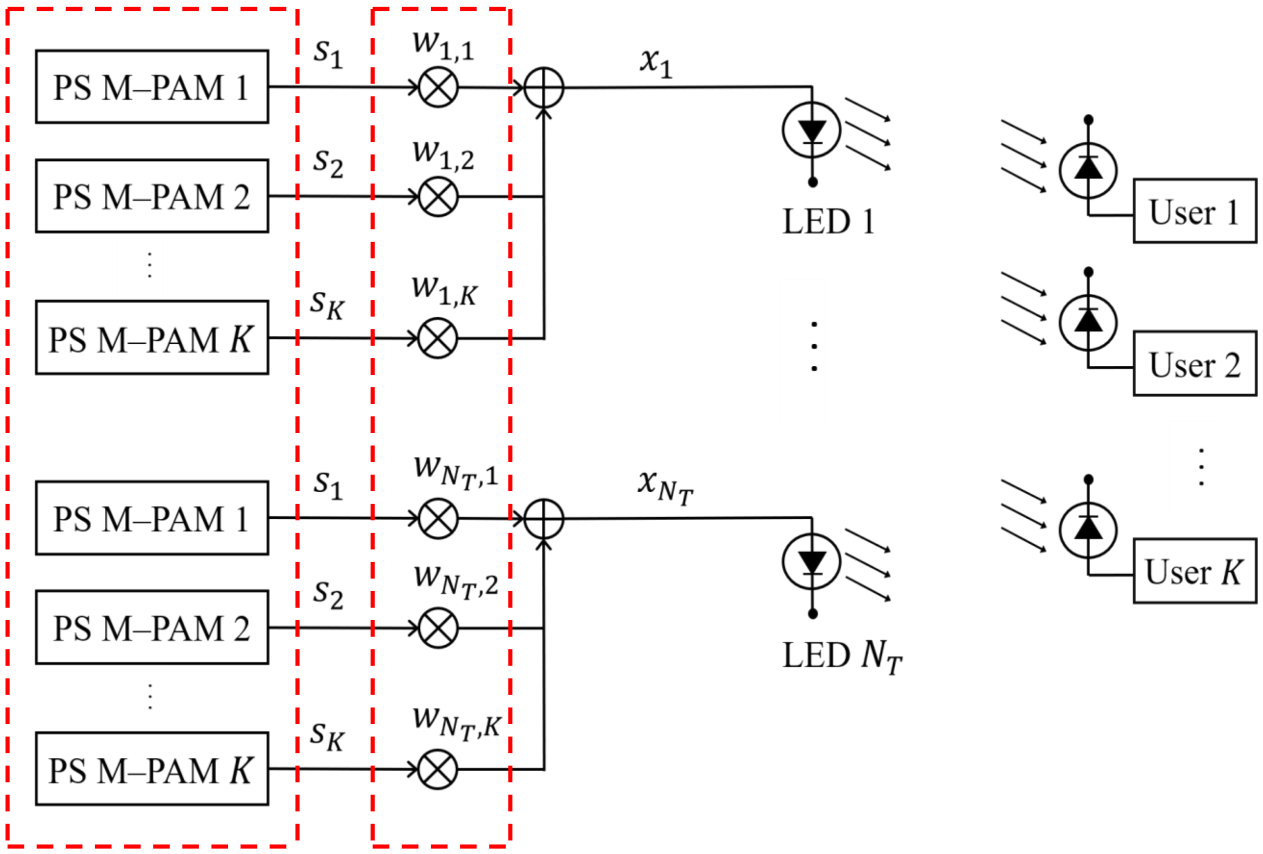
With $k \in \{1, 2, \dots, K\}, m_k \in \{1, 2, \dots, M\}$),

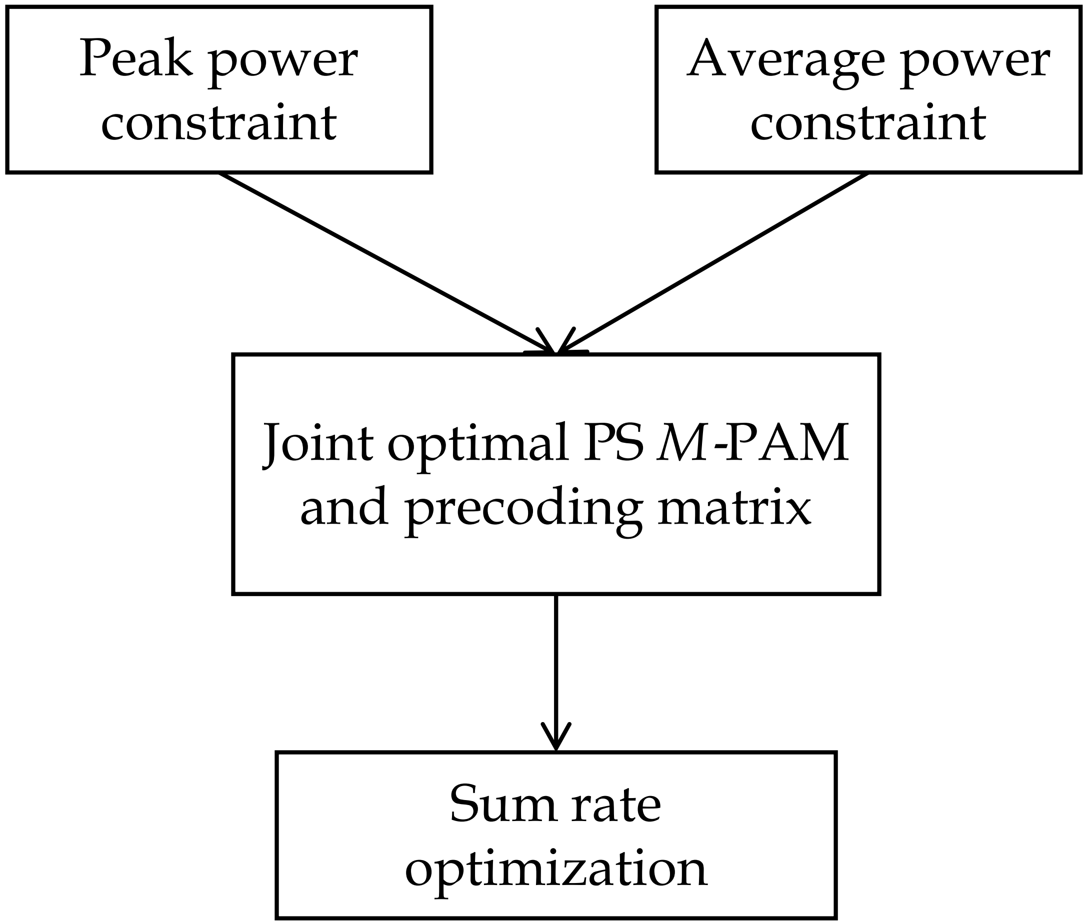
$s_k \sim \{s_{k,m_k}\}$: s_k is a data symbol drawn from the PS M-PAM k with an amplitude a_{k,m_k} and the corresponding probability p_{k,m_k}.

PS M–PAM k

- Amplitude vector: $\boldsymbol{a_k} = [a_{k,1} \quad a_{k,2} \cdots \quad a_{k,M}]$
  - → Fixed value based on LED's peak power
- Probability mass function vector: $\boldsymbol{p_k} = [p_{k,1} \quad p_{k,2} \cdots \quad p_{k,M}]$
  - → $\boldsymbol{p_k}$ can be optimized to improve the sum-rate performance

System model





System model

❑ Problem formulation

$$\mathbb{P}1: \underset{\mathbf{P},\mathbf{W}}{\text{maximize}} \quad \sum_{k=1}^{K} R_k(\mathbf{P},\mathbf{W})$$ → Sum rate maximization

subject to

$$\sum_{k=1}^{K} \mathbf{a}_k^T \mathbf{p}_k \mathbb{1}_{N_T\times 1}^T \mathbf{w}_k \le \mathcal{E},$$ → Average power constraint

$$\left\| [\mathbf{W}]_{n,:} \right\|_1 \le 1, \ \forall n \in \{1, 2, \cdots, N_T\},$$ → Peak power constraint

$$\mathbf{0}_{K\times M} \le \mathbf{P} \le \mathbb{1}_{K\times M},$$

$$\mathbf{P} \times \mathbb{1}_{M\times 1} = \mathbb{1}_{K\times 1},$$

- $0 < \alpha = \frac{\varepsilon}{N_T A} \le 1$ is power ratio
- $\mathbf{P} = [\boldsymbol{p}_1 \ \ \boldsymbol{p}_2 \cdots \ \boldsymbol{p}_K]$: PMF matrix of K PS M-PAM constellation
- $\mathbf{W} = [\boldsymbol{w}_1 \ \ \boldsymbol{w}_2 \cdots \ \boldsymbol{w}_K]$: precoding matrix

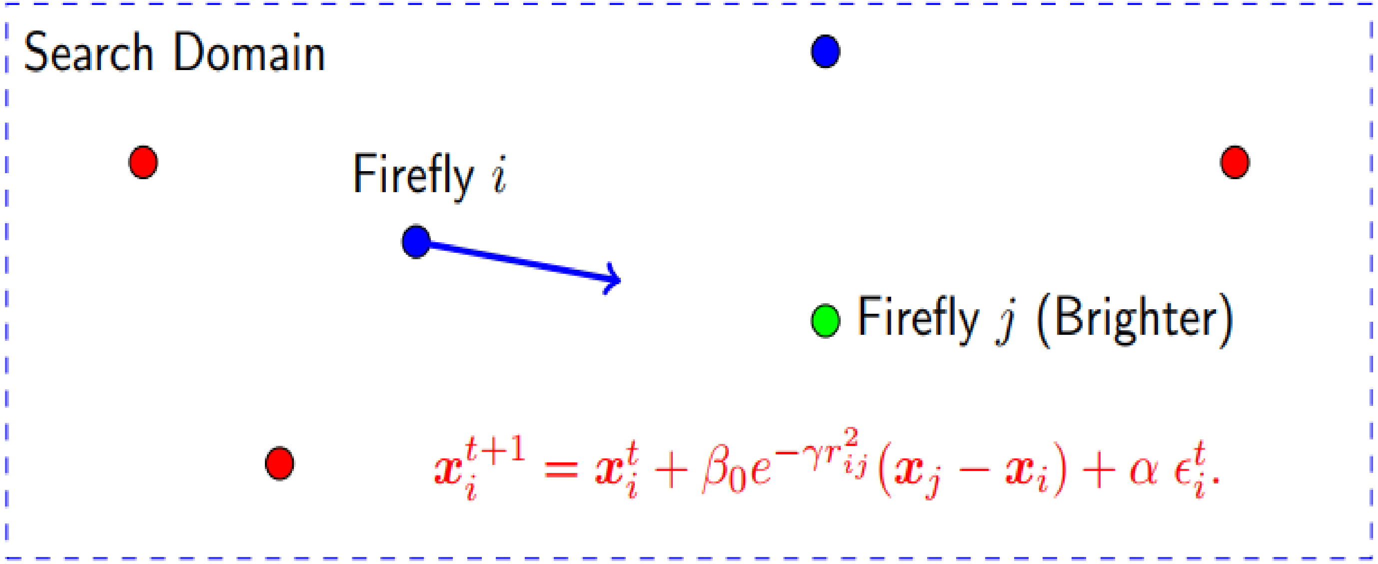
➡ Non-convex problem with multiple variables

Firefly algorithm

- The firefly algorithm (FA) was developed by Prof. Xin-She Yang in 2008
- It is a Nature-Inspired Optimization Algorithms (metaheuristic algorithm)

Firefly Behaviors and Idealization (Yang, 2008)
▪ Fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex
▪ The attractiveness is proportional to the brightness and they both decrease as their distance increases. ▪ For any two flashing fireflies, the less brighter one will move towards the brighter one.
▪ If no brighter firefly can be seen, a firefly will move randomly.

Firefly algorithm



- The objective landscape maps to a light-based landscape and fireflies swarm into the brightest points/regions.
- For a maximization problem, the brightness can simply be proportional to the value of the objective function.

- x_i^t is the solution vector (or position of firefly i) in the search space at iteration t
- β_0 is the attractiveness at zero distance (i.e., $r_{ij} = 0$)
- γ is the absorption coefficient
- ϵ_i^t is the random vector drawn from a normal distribution
- α is the scaled factor

Firefly algorithm - Algorithmic Equation of FA

❖ Attractiveness

The attractiveness β of a firefly is given by:

$$\beta = \beta_0 e^{-\gamma r^2}$$

where β_0 is the attractiveness at zero distance ($r = 0$).

❖ Distance

The distance between any two fireflies $\boldsymbol{i}$ and $\boldsymbol{j}$ at $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ at t-th generation, respectively, is the Cartesian distance:

$$r_{ij} = ||\boldsymbol{x}_i^{(t)} - \boldsymbol{x}_j^{(t)}||$$

❖ Movement of the firefly $\boldsymbol{i}$ with less brighter to brighter one $\boldsymbol{j}$ (update new solution)

$$\boldsymbol{x}_i = \boldsymbol{x}_i + \beta_0 e^{-\gamma r_{ij}^2}\left(\boldsymbol{x}_j^{(t)} - \boldsymbol{x}_i^{(t)}\right) + \alpha^{(t)}\epsilon^{(t)}$$

➡ It tends to be a global optimizer but can be potentially more computationally expensive

Firefly algorithm - Algorithmic Equation of FA

- Problem reformulation: adopt penalty method

Original problem	Reformulated problem
$\mathbb{P}\mathbf{1}: \underset{\mathbf{P},\mathbf{W}}{\text{maximize}} \sum_{k=1}^{K} R_k(\mathbf{P},\mathbf{W})$ subject to $\sum_{k=1}^{K} \mathbf{a}_k^T \mathbf{p}_k \mathbb{1}_{N_T\times 1}^T \mathbf{w}_k \leq \mathcal{E},$ $\left\|[\mathbf{W}]_{n,:}\right\|_1 \leq 1, \forall n \in \{1, 2, \cdots, N_T\},$ $\mathbf{0}_{K\times M} \leq \mathbf{P} \leq \mathbb{1}_{K\times M},$ $\mathbf{P}\times \mathbb{1}_{M\times 1} = \mathbb{1}_{K\times 1},$	$\mathbb{P}\mathbf{2}: \underset{\mathbf{P},\mathbf{W}}{\text{maximize}} \sum_{k=1}^{K} R_k(\mathbf{P},\mathbf{W}) - P(\mathbf{P},\mathbf{W}),$ where $P(\mathbf{P},\mathbf{W})$ is the penalty term given as $P(\mathbf{P},\mathbf{W}) = \lambda_1 \max\left(0, \sum_{k=1}^{K} \mathbf{a}_k^T \mathbf{p}_k \mathbb{1}_{N_T\times 1}^T \mathbf{w}_k - \mathcal{E}\right)^2$ $+\lambda_2 \sum_{n=1}^{N_t} \max\left(0, \left\|[\mathbf{W}]_{n,:}\right\|_1 - 1\right)^2$ $+\lambda_3 \sum_{k=1}^{K}\sum_{m=1}^{M} \min\left(0, p_{k,m}\right)^2 + \lambda_3 \sum_{k=1}^{K}\sum_{m=1}^{M} \max\left(0, p_{k,m}-1\right)^2$ $+\lambda_4 \sum_{k=1}^{K} \max\left(0, \left\|[\mathbf{P}]_{k,:}\right\|_1 - 1\right)^2$ where λ_j are penalty constants.

Firefly algorithm

The objective landscape maps to a light-based landscape
and fireflies swarm into the brightest points/regions.

Algorithm 1 Firefly algorithm

Generate N populations $\{(\mathbf{W}_1,\mathbf{P}_1),\cdots,(\mathbf{W}_N,\mathbf{P}_N)\}$ randomly.
Evaluate the light intensities of N population $I(\mathbf{W}_i,\mathbf{P}_i)\ \forall i \in [1,N]$.
Rank the fireflies in descending order of light intensities $I(\mathbf{W}_i,\mathbf{P}_i)$.
Define the current best solution: $I^* := I(W^*,P^*)$.
for $t=1\ :\ T$ **do**
  for $m=1\ :\ N$ **do**
    for $n=1\ :\ N$ **do**
      if $I(\mathbf{W}_n,\mathbf{P}_n) > I(\mathbf{W}_m,\mathbf{P}_m)$ **then**
        1. Move firefly m toward firefly n
        2. Update the light intensity of firefly m with new $(\mathbf{W}_m,\mathbf{P}_m)$
      end if
    end for
  end for
  Rank the fireflies in descending order of $I(\mathbf{W}_i,\mathbf{P}_i)$.
  Update the current best solution $I^* := I(W^*,P^*)$
end for
return (W^*,P^*).

The light intensity of the firefly i, $(\mathbf{W}_i,\mathbf{P}_i)$ is given as

$$I(\mathbf{W}_i,\mathbf{P}_i) = \sum_{k=1}^{K} R_k(\mathbf{W}_i,\mathbf{P}_i) - P(\mathbf{W}_i,\mathbf{P}_i).$$

For any fireflies m and n amongst the population in the generation t. If $I(\mathbf{W}_n^{(t)},\mathbf{P}_n^{(t)}) > I(\mathbf{W}_m^{(t)},\mathbf{P}_m^{(t)})$, the firefly m will move toward the firefly n as

$$\mathbf{W}_m^{(t)} = \mathbf{W}_m^{(t)} + \beta_0 \exp\left(-\gamma \left(r_{\mathbf{W},mn}^{(t)}\right)^2\right)\left(\mathbf{W}_n^{(t)} - \mathbf{W}_m^{(t)}\right) + \alpha^{(t)}\mathbf{V}_1,$$

$$\mathbf{P}_m^{(t)} = \mathbf{P}_m^{(t)} + \beta_0 \exp\left(-\gamma \left(r_{\mathbf{P},mn}^{(t)}\right)^2\right)\left(\mathbf{P}_n^{(t)} - \mathbf{P}_m^{(t)}\right) + \alpha^{(t)}\mathbf{V}_2,$$

where $r_{\mathbf{W},mn}^{(t)} = \left\|\mathbf{W}_n^{(t)} - \mathbf{W}_m^{(t)}\right\|$ and $r_{\mathbf{P},mn}^{(t)} = \|\mathbf{P}_n - \mathbf{P}_m\|$ are the Cartesian distances, $V_1 \in \mathbb{R}^{N_T \times K}$, $V_2 \in \mathbb{R}^{K \times M}$ are random matrixes whose elements are drawn from a normal distribution.

Firefly algorithm

❑ Scenario and system parameters

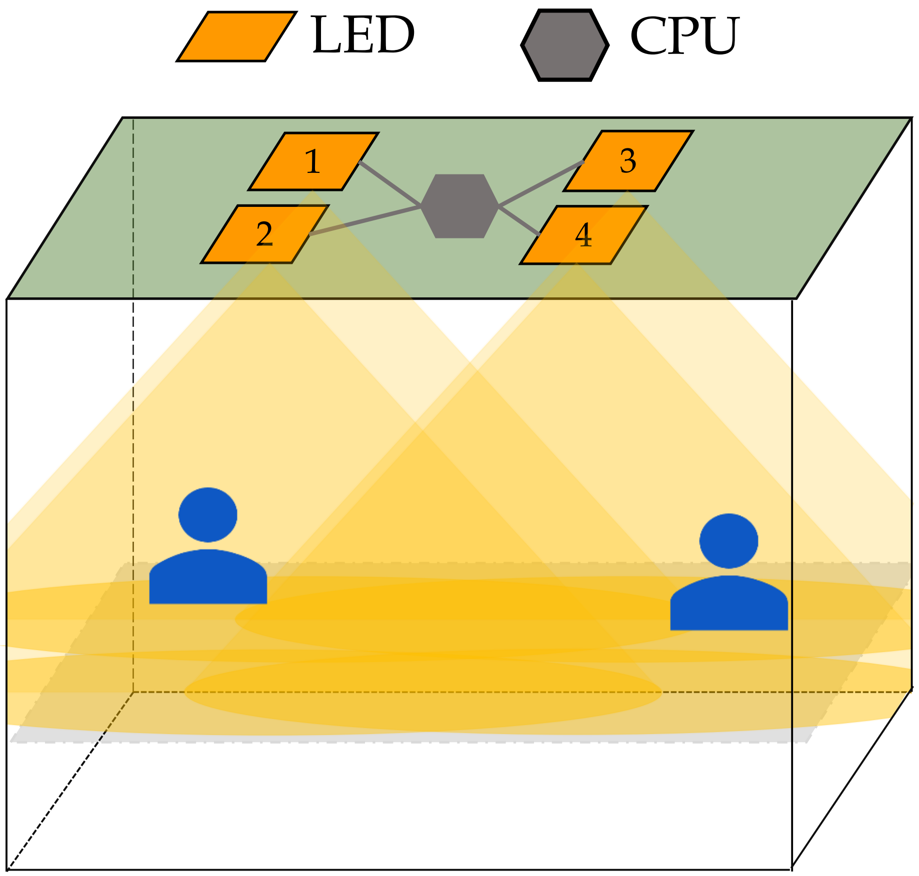
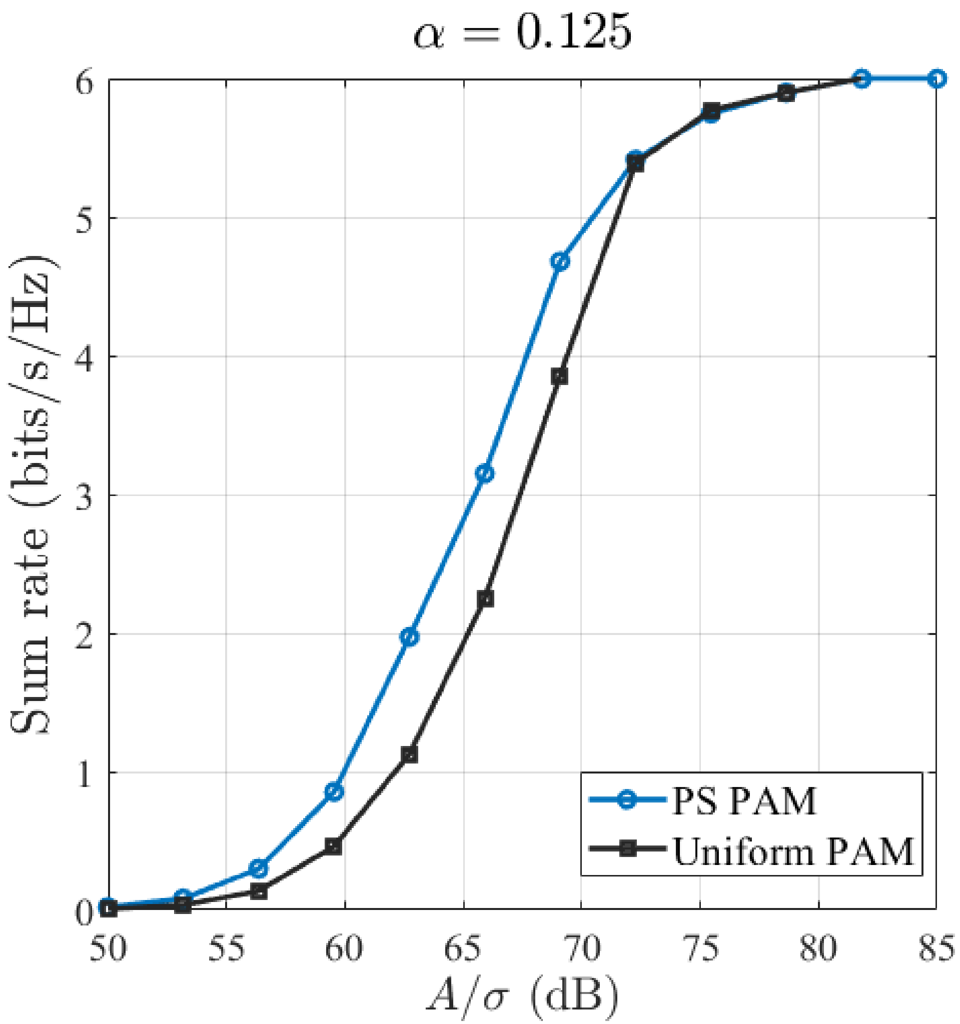


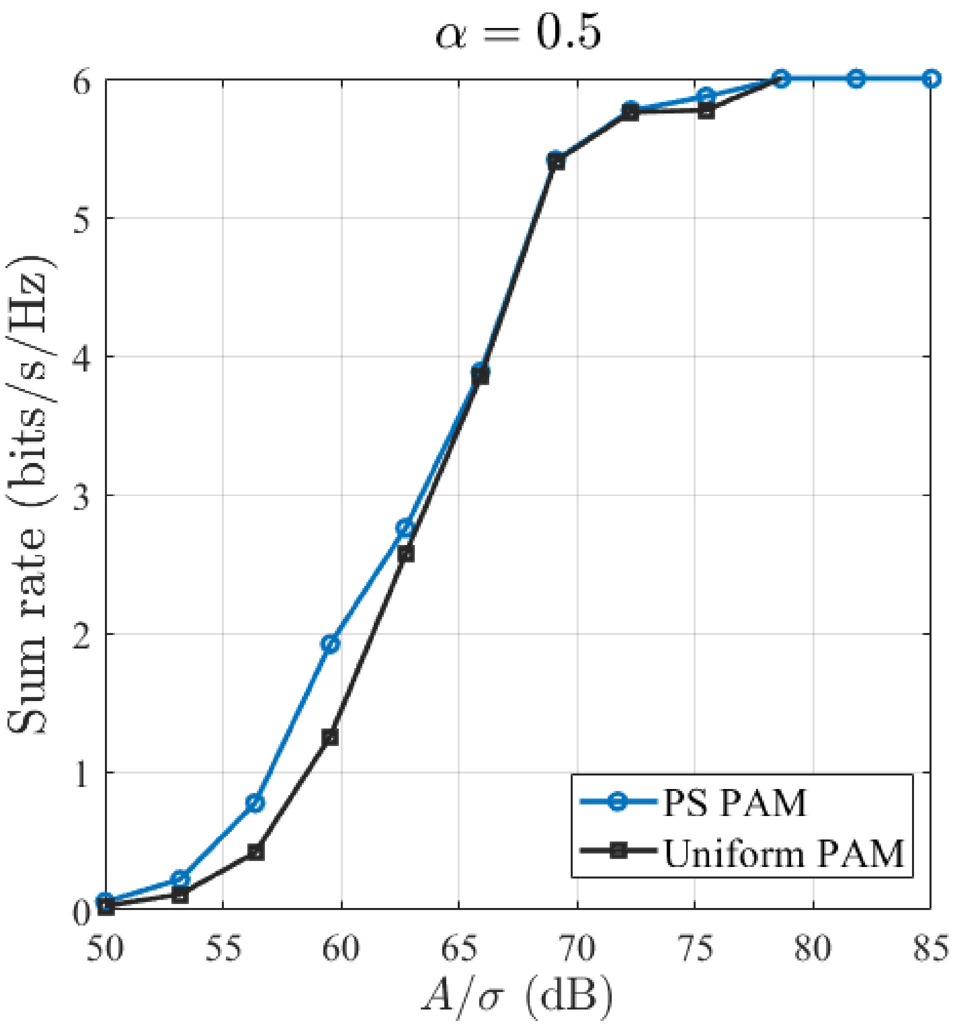
Table 1: System Parameters

Room and LED configurations	
Room dimension (Length × Width × Height)	5 (m) × 5 (m) × 3 (m)
LED positions	luminary 1 : $\left(-\sqrt{2},-\sqrt{2},3\right)$, luminary 2 : $\left(\sqrt{2},-\sqrt{2},3\right)$ luminary 3 : $\left(\sqrt{2},\sqrt{2},3\right)$, luminary 4 : $\left(-\sqrt{2},\sqrt{2},3\right)$
LED bandwidth, B	20 MHz
LED beam angle, ϕ	120° (LED Lambertian order is 1)
LED conversion factor, η	0.44 W/A
Receiver photodetectors	
Active area, A_r	1 cm^2
Responsivity, γ	0.54 A/W
Field of view (FOV), Ψ	60°
Optical filter gain, $T_s(\psi)$	1
Refractive index of the concentrator, κ	1.5
Noise variance, σ^2	1
Other parameters	
Ambient light photocurrent, χ_{amp}	10.93 $A/(m^2 \cdot Sr)$
Preamplifier noise current density, i_{amp}	5 $pA/Hz^{-1/2}$

Results

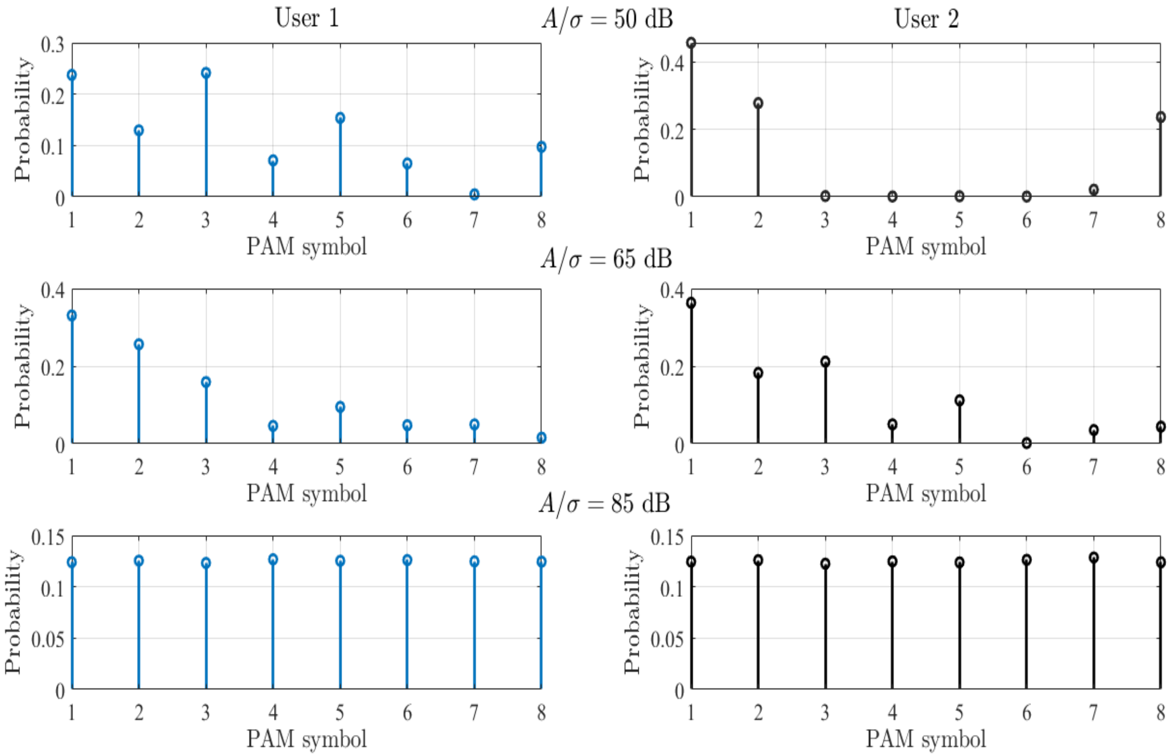
- Sum rate versus peak amplitude



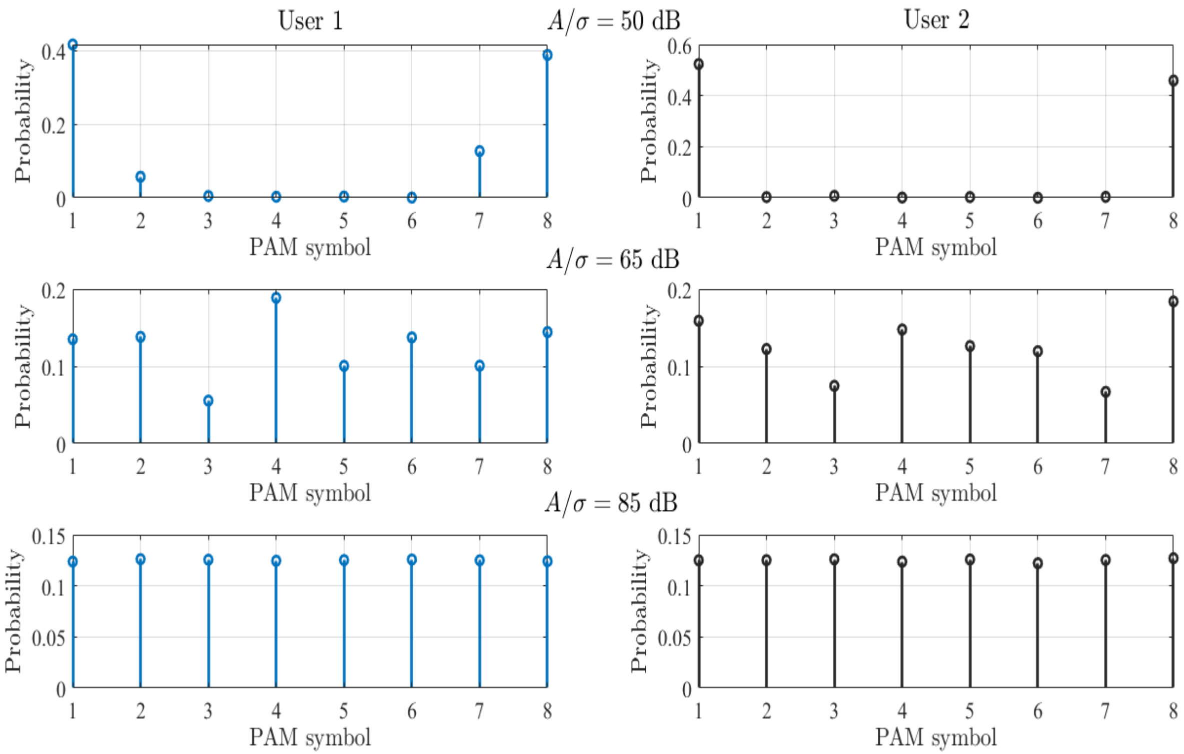


Results

- Optimal PS - 8PAM



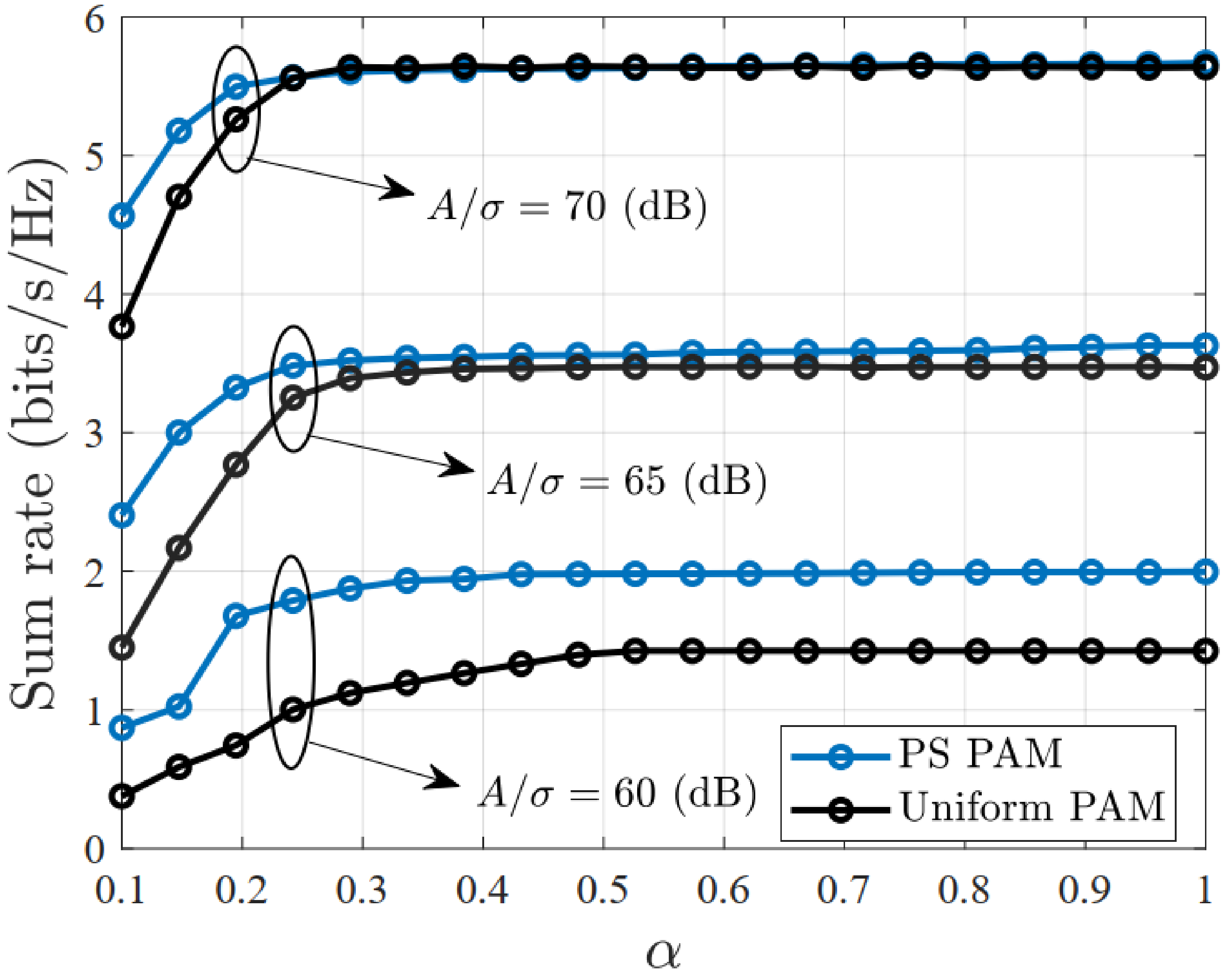
(a) $\alpha = 0.125$



(a) $\alpha = 0.5$

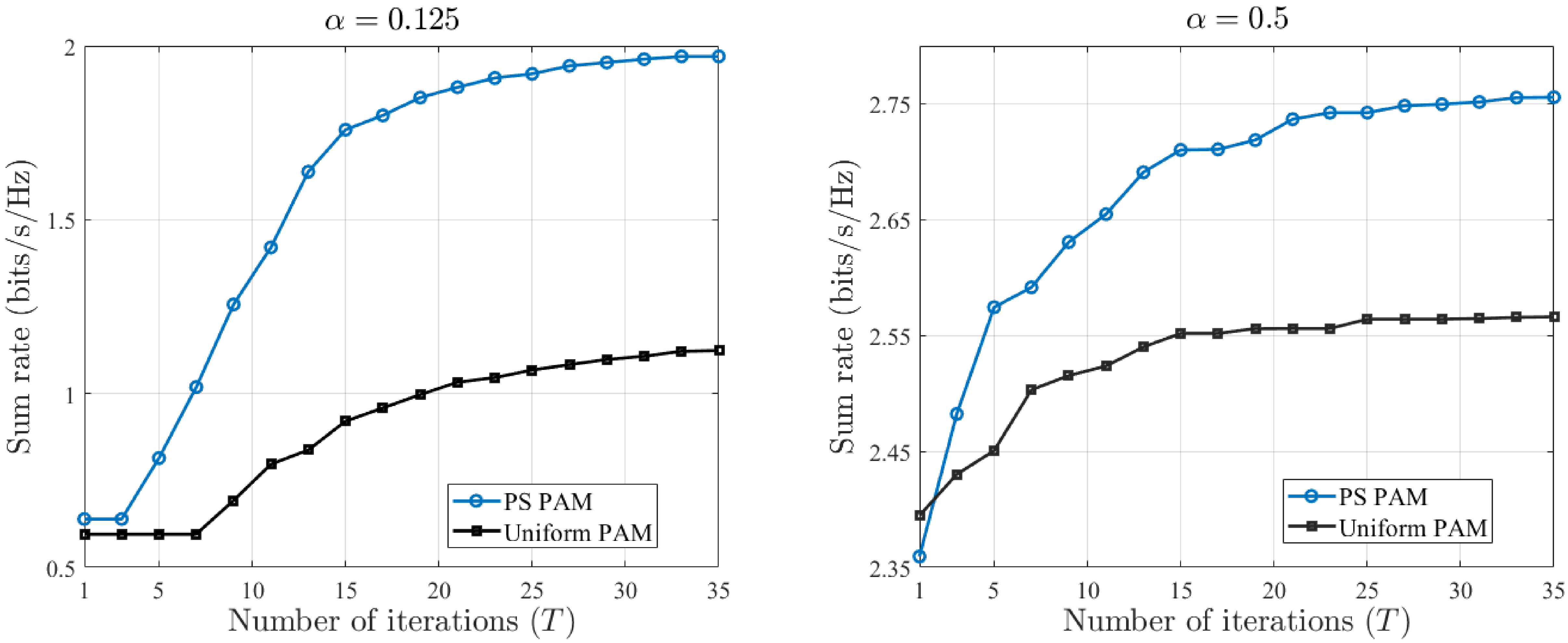
Results

- Sum rate versus power ratio α



Results

- Convergence of FA algorithm



$A/\sigma = 62$ dB

Unsolved problem

General precoding + PS PAM design	ZF precoding + PS PAM design
Alternative optimization: Decouple joint design problem into two sub problem with each variable 1. Sub-problem with P is non-convex: • Solve by Convex-Concave Procedure (CCP) 2. Sub-problem with W is non-convex: unsolved	**Alternative optimization:** Decouple joint design problem into two sub problem with each variable 1. Sub-problem with P is convex: • Solve by Convex Optimization 2. Sub-problem with W is non-convex: unsolved

Thank you for listening!

Q & A